Smart management strategies of utility-scale energy storage systems in power networks

Choton Kanti Das

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Smart Management Strategies of Utility-scale Energy Storage Systems in Power Networks

Choton Kanti Das
School of Engineering
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Doctor of Philosophy (PhD)

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USE OF THESIS

The Use of Thesis statement is not included in this version of the thesis.
Abstract

Power systems are presently experiencing a period of rapid change driven by various interrelated issues, e.g., integration of renewables, demand management, power congestion, power quality requirements, and frequency regulation. Although the deployment of Energy Storage Systems (ESSs) has been shown to provide effective solutions to many of these issues, misplacement or non-optimal sizing of these systems can adversely affect network performance. This present research has revealed some novel working strategies for optimal allocation and sizing of utility-scale ESSs to address some important issues of power networks at both distribution and transmission levels. The optimization strategies employed for ESS placement and sizing successfully improved the following aspects of power systems: performance and power quality of the distribution networks investigated, the frequency response of the transmission networks studied, and facilitation of the integration of renewable generation (wind and solar). This present research provides effective solutions to some real power industry problems including minimization of voltage deviation, power losses, peak demand, flickering, and frequency deviation as well as rate of change of frequency (ROCOF).

Detailed simulation results suggest that ESS allocation using both uniform and non-uniform ESS sizing approaches is useful for improving distribution network performance as well as power quality. Regarding performance parameters, voltage profile improvement, real and reactive power losses, and line loading are considered, while voltage deviation and flickers are taken into account as power quality parameters. Further, the study shows that the PQ injection-based ESS placement strategy performs better than the P injection-based approach (in relation to performance improvement), providing more reactive power compensations. The simulation results also demonstrate that obtaining the power size of a battery ESS (MVA) is a sensible approach for frequency support. Hence, an appropriate sizing of grid-scale ESSs including tuning of parameters $K_p$ and $T_p$ (active part of the PQ controller) assist in improving the frequency response by providing necessary active power. Overall, the proposed ESS allocation and sizing approaches can underpin a transition plan from the current power grid to a future one.
Keywords: Energy storage system; Energy storage system placement; Energy storage system sizing; Battery storage; Optimal allocation; Optimal placement; Optimal sizing; Voltage profile; Power quality; Power losses; Line loading; Flicker; Frequency response; Rate of change of frequency; ROCOF; DIgSILENT PowerFactory; Python; Cost optimization; Meta-heuristic optimization; Heuristic optimization; Artificial bee colony optimization; Particle swarm optimization; PSO; Transmission network planning; Distribution network planning; Transmission network; Distribution network.
Declaration

I, Choton Kanti Das, hereby declare that this thesis does not, to the best of my belief and knowledge:

- Incorporate without acknowledgement any material previously submitted for a degree or diploma in any institution of higher education;

- Contain any material published previously or written by another person except where due reference is made in the text; or contain any defamatory material.

Signed: Choton Kanti Das
Dated: 04.06.2019
I would like to dedicate this thesis to my loving parents.
Acknowledgements

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Glossary

**β**<sub>ESS</sub> Cost weighting factor in relation to ESSs

**β**<sub>LLd</sub> Cost weighting factor in relation to line loading

**β**<sub>PLs</sub> Cost weighting factor in relation to power losses

**β**<sub>VDev</sub> Cost weighting factor in relation to voltage deviation

**Δt** Interval of time

**Δt** Time interval

**δ**<sub>i</sub>, **δ**<sub>j</sub> Voltage angle of bus **i** & **j**

**η**<sup>c</sup> Charging efficiency of an ESS

**η**<sup>d</sup> Discharging efficiency of an ESS

**η**<sub>C</sub> Charging efficiency of an ESS

**η**<sub>D</sub> Discharging efficiency of an ESS

**η**<sub>c</sub> ESS charging efficiency

**η**<sub>d</sub> ESS discharging efficiency

**γ**<sub>VDev</sub> Cost weighting factor in relation to voltage deviation

**Γ**<sub>LL</sub> Cost rate for line loading

**Γ**<sub>LL</sub> Weighting factor for line loading cost

**Γ**<sub>loss</sub> Power loss cost rate

**γ**<sub>LLs</sub> Cost rate for line loading

**γ**<sub>PL</sub> Weighting factor for power losses cost

**γ**<sub>VD</sub> Cost rate for voltage deviation

**γ**<sub>VD</sub> Weighting factor for voltage deviation cost

**Π**<sub>n</sub> Load weighting factor of bus **n**

**ψ**<sub>k</sub> Network impedance angle (degrees)

**ζ**<sub>i</sub> Load weighting factor of **i**th bus

**ζ**<sub>n</sub> Load weighting factor of **n**th bus

**λ**<sub>ESS</sub><sup>n</sup> A variable for representing an ESS position in the network

**λ**<sub>ESS</sub> Variable that represents ESS position in the network

**J**<sub>(C_{Fi})</sub> Objective function which is a function of cost

**σ**<sup>ABC</sup> & **σ**<sup>FSCABC</sup> Standard deviation of objective functions using ABC & FSCABC approaches, respectively

**aP**, **bP**, & **cP** Coefficients for real power of phase **a**, **b**, & **c**

**aP**, **bP**, & **cP** Coefficients for real power of phase **a**, **b**, & **c**

**aQ**, **bQ**, & **cQ** Coefficients for reactive power of phase **a**, **b**, & **c**

**aQ**, **bQ**, & **cQ** Coefficients for reactive power of phase **a**, **b**, & **c**
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
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<td>$aQ$, $bQ$, &amp; $cQ$</td>
<td>Reactive power coefficients for phase $a$, $b$, &amp; $c$</td>
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<tr>
<td>$C^{uu}$</td>
<td>Cost of an UltraBattery unit</td>
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<tr>
<td>$c_F^d(\psi_k, v_a)$</td>
<td>Flicker coefficient</td>
</tr>
<tr>
<td>$C_{LL}^d$</td>
<td>Cost in relation to line loading</td>
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<tr>
<td>$C_{LL}^l$</td>
<td>Cost in relation to line loading</td>
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<td>$C_{PL}^d$</td>
<td>Cost in relation to power losses</td>
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<td>Cost in relation to voltage deviation</td>
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<td>$C_{PL}^l$</td>
<td>Cost for power losses</td>
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<tr>
<td>$C^{UU}$</td>
<td>Unit cost for UltraBattery</td>
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<tr>
<td>$C_{n}^{VDev}$</td>
<td>Cost in relation to voltage deviation</td>
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<td>$E_{ESS}$</td>
<td>ESS energy</td>
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<td>$E_{ESS}^{\text{max}}$</td>
<td>Maximum energy of an ESS</td>
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<td>$E_{ESS}^{\text{min}}$</td>
<td>Minimum energy of an ESS</td>
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<td>$E_{ESS}^{\text{MAX}}$</td>
<td>Maximum ESS energy</td>
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<td>$E_{ESS}^{\text{+}}$</td>
<td>Energy of an ESS</td>
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<td>$E_{ESS}^{\text{t+1}}$</td>
<td>ESS energy at time $t+1$</td>
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<td>$E_{ESS}^{\text{t}}$</td>
<td>ESS energy at time $t$</td>
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<tr>
<td>$I_{ij}^{\text{max}}$</td>
<td>Current limit of line $ij$</td>
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<td>$I_{ij}^{l}$</td>
<td>Current magnitude through line $ij$</td>
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<tr>
<td>$I_{max}$</td>
<td>Maximum iteration number of the FS-CABC optimization approach</td>
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<td>$I_{t}^{\text{max}}$</td>
<td>Maximum iteration number in FS-CABC optimization</td>
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<td>$I_{t}^{\text{max}}$</td>
<td>Maximum number of iterations in ABC optimization</td>
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<tr>
<td>$K$</td>
<td>Total number of active ESSs on the network</td>
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<tr>
<td>$k_{t}^{\text{step}}(\psi_k)$</td>
<td>Step factor of flicker disturbance</td>
</tr>
<tr>
<td>$k_v(\psi_k)$</td>
<td>Factor for voltage change during switching operation of a wind DG (WDG)</td>
</tr>
<tr>
<td>$L_{\text{trial}}$</td>
<td>Trial limit to improve a food source in FSCABC optimization</td>
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<tr>
<td>$L_{\text{TRIAL}}$</td>
<td>Trial limit to improve a food source in FSCABC optimization</td>
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<td>$l_{t}^{\text{trial}}$</td>
<td>Trial limit for improving a food source in ABC optimization</td>
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<tr>
<td>$LB_1$</td>
<td>Lower limit of decision variable $S_{ESSP}^n$</td>
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<td>$lb_1$</td>
<td>Lower boundary of decision variable $S_{ESS}^n$</td>
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<td>$lb_1$</td>
<td>Lower limit of decision variable $S_{ESSP}^n$</td>
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<td>$LB_2$</td>
<td>Lower limit of decision variable $S_{ESSQ}^n$</td>
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<td>$lb_2$</td>
<td>Lower boundary of decision variable $\lambda_{ESS}^n$</td>
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<td>$lb_2$</td>
<td>Lower limit of decision variable $S_{ESSQ}^n$</td>
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<td>$LB_3$</td>
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<td>$lb_3$</td>
<td>Lower boundary of decision variable $\lambda_{ESS}^n$</td>
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<td>Total number of lines in the network</td>
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**GLOSSARY**

$N^D$ Number of decision variables in FS-CABC optimization

$N_{10}$ Number of switching operations in a 10-minute period

$N_{120}$ Number of switching operations in a 120-minute period

$N_D$ Number of decision variables in ABC optimization

$N_{FS}$ Number of food sources in ABC optimization

$P$ Active power

$P_{ESS-max}$ Maximum power of an ESS

$P_{ESS-min}$ Minimum power of an ESS

$P_{ESS}$ Power of an ESS

$P^{LT}$ Total active power loss of the system

$P^L(i,j)$ Active power loss of a line linking two adjacent buses, $i$ and $j$

$P^{T-F}$ Input real power (MW) of the feeder

$P_{ESS-max}$ Maximum power of an ESS

$P_{ESS-min}$ Minimum power of an ESS

$P_{ESS}$ ESS power

$P_{ESS}$ Power of an ESS

$P^D_{i\rightarrow k}$ Real power delivered from $i$ to a neighbouring bus $k$

$P^{del}_{i\rightarrow k}$ Active power delivered from $i$ to adjacent bus $k$

$P^{D}_{i\rightarrow k}$ Real power delivered from $i$ to a adjacent bus $k$

$P^{d}_{i\rightarrow k}$ Real power delivered from $i$ to a neighbouring bus $k$

$P_i$ Active power flowing out of bus $i$

$P^C_i$ Consumed real power at bus $i$

$P^C$ Consumed active power at bus $i$

$P^{gen}_i$ Real power generated by bus $i$

$P_{gen}$ Generated active power at bus $i$

$P^G_i$ Generated real power at bus $i$

$P_i^g$ Real power generated at bus $i$

$P^D_{j\rightarrow i}$ Power delivered to $i$ from a neighbour bus $j$

$P^{del}_{j\rightarrow i}$ Power delivered to $i$ from an adjacent bus $j$

$P^D_{j\rightarrow i}$ Power delivered to $i$ from a adjacent bus $j$

$P^d_{j\rightarrow i}$ Power delivered to $i$ from a neighbouring bus $j$

$P^L_{L-base}$ Real power loss for base case (without ESS)

$P^L_{L-ESS}$ Real power loss with optimal ESS placement

$P^L_{L-ESS}$ Real power loss through optimal ESS allocation

$P^L_{L}$ Total real power loss

$P^L_{L}$ Total active power loss

$P^L(i,j)$ Active power loss of a line connecting two buses, $i$ and $j$

$P^L(i,j)$ Real power loss of a line connecting two buses, $i$ and $j$

$P^L^{base}_{L}$ Active power loss without ESS placement (base case)

$P^L_{L-ESS}$ Active power loss through optimal ESS allocation

$P^{FC}\text{Cont}$ Flicker disturbance for continuous operation of WDGs

$P^{FC}\text{Cont}$ Flicker disturbance for continuous operation of WDGs

$P^{FSw}$ Flicker disturbance for switching operation of WDGs

$P^{LT}\text{Cont}$ Long-term flicker disturbance factor for continuous operation of WDGs

$P^{LTSw}$ Factor for long-term flicker disturbance during switching operation of WDGs
GLOSSARY

$P_{\text{STCont}}^n$ Short-term flicker disturbance factor for continuous operation of WDGs

$P_{\text{STSw}}^n$ Factor for short-term flicker disturbance during switching operation of WDGs

$P_{t-F}$ Input real power (MW) of the feeder

$P_{t-ESS,C}$ Charging power of an ESS at time $t$

$P_{t-ESS,D}$ Discharging power of an ESS at time $t$

$P_{t-ESS}$ ESS power at time $t$

$P_{t-BESS,C}$ BESS charging power at time $t$

$P_{t-BESS,D}$ BESS discharging power at time $t$

$P_{t-BESS}$ BESS power at time $t$

$P_{t-ESS}^\text{−max}$ Maximum power factor (p.f.) on the dispatch of an ESS

$P_{t-ESS}^\text{−min}$ Minimum p.f. on the dispatch of an ESS

$P_{t-ESS}^\text{−max}$ Maximum power factor (p.f.) on the dispatch of nth ESS

$P_{t-ESS}^\text{−min}$ Minimum p.f. boundary on the dispatch of ESSs

$P_{t-ESS}^n$ Power factor (p.f.) on the dispatch of an ESS on bus $n$

$PLRI_{P-ESS}^P$ Index for real power loss reduction through optimal ESS allocation

$PLRI_P$ Real power loss reduction index with optimal ESS placement

$PLRI_{Q-ESS}^Q$ Index for reactive power loss reduction through optimal ESS allocation

$PLRI_Q$ Reactive power loss reduction index with optimal ESS placement

$PLRI_{T-ESS}^T$ Index for total power loss reduction through optimal ESS allocation

$PLRI_T$ Total power loss reduction index with optimal ESS placement

$PLT_{w-ESS}^T$ Total power loss of the system through optimal ESS allocation

$PLT_{w0-ESS}^T$ Total power loss of the system without ESS allocation

$Q$ Reactive power

$Q^L_T$ Total reactive power loss of the system

$Q^L(i,j)$ Reactive power loss of a line linking two adjacent buses, $i$ and $j$

$Q^T_{i→-P}$ Input reactive power (MVar) of the feeder

$Q_{i→k}^{\text{Del}}$ Reactive power delivered from $i$ to a neighbouring bus $k$

$Q_{i→k}^{\text{Del}}$ Reactive power delivered from $i$ to adjacent bus $k$

$Q_{i→k}^D$ Reactive power delivered from $i$ to a adjacent bus $k$

$Q_{i→k}^d$ Reactive power delivered from $i$ to a neighbouring bus $k$

$Q_i$ Reactive power flowing out of bus $i$

$Q_{i-\text{Con}}^C$ Reactive power consumed by bus $i$

$Q_{i-\text{Con}}^{\text{Gen}}$ Consumption reactive power at bus $i$

$Q_i^C$ Consumed reactive power at bus $i$

$Q_i^G$ Generated reactive power at bus $i$

$Q_{i-\text{Gen}}^{\text{Con}}$ Generated reactive power at bus $i$
GLOSSARY

\( Q^g_i \) Reactive power generated at bus \( i \)
\( Q^D_{j \rightarrow i} \) Reactive power delivered to \( i \) from a neighbour bus \( j \)
\( Q_{j \rightarrow i}^{del} \) Reactive power delivered to \( i \) from a adjacent bus \( j \)
\( Q^d_{j \rightarrow i} \) Reactive power delivered to \( i \) from a neighbour bus \( j \)
\( Q^L_{base} \) Reactive power loss for base case (without ESS)
\( Q^L_{ESS} \) Reactive power loss with optimal ESS placement
\( Q^L_{ESS-base} \) Reactive power loss without ESS allocation (base case)
\( Q^L_{ESS-base} \) Reactive power loss through optimal ESS allocation
\( Q_T \) Total reactive power loss
\( Q_{L(i,j)} \) Reactive power loss of a line connecting two buses, \( i \) and \( j \)
\( Q_{L(i,j)} \) Reactive power loss of a line linking two buses, \( i \) and \( j \)
\( Q^L_{base} \) Reactive power loss without ESS placement (base case)
\( Q^L_{ESS} \) Reactive power loss through optimal ESS allocation
\( S^{app} \) Apparent power
\( S^{ESS-max} \) Maximum size of an ESS
\( S^{ESS-min} \) Minimum size of an ESS
\( S^{ESS-nom} \) Nominal apparent power (MVA) of an ESS
\( S^{ESS} \) Size of an ESS in MWh
\( S^{PV-max} \) Rated capacity (kVA) of solar DGs
\( S^{PV-op} \) Operational capacity (kVA) of solar DGs
\( S^{WDG} \) Rated apparent power of the wind turbine (VA)
\( S^{wind} \) Total capacity (kVA) of a WDG
\( S^{ESS-MAX} \) Maximum size of an ESS
\( S^{ESS-max} \) Maximum ESS size
\( S^{ESS-min} \) Minimum size of an ESS
\( S^{ESS} \) Size of an ESS in MWh
\( S^{ESS} \) Total size (MVA) of an ESS in \( n \)th bus
\( S^{ESSP} \) Real power (MW) injected by an ESS to \( n \)th bus
\( S^{ESSQ} \) Reactive power (MVar) injected by an ESS to \( n \)th bus
\( S^{PV-MAX} \) Solar DGs’ rated capacity (kVA)
\( S^{PV-OP} \) Solar DGs’ operational capacity (kVA)
\( S^{wind} \) Wind DGs’ total capacity (kVA)
\( S^{grid} \) Short circuit apparent power of the grid (VA)
\( S^L \) Load at \( n \)th bus (p.u.)
\( S_{Li} \) Load at \( i \)th bus
\( S^{ESSP} \) Injected real power (MW) by the ESS to the \( n \)th bus
\( S^{ESSQ} \) Injected reactive power (MVar) by the ESS to the \( n \)th bus
\( S^{ESS} \) Total ESS size (MVA) in \( n \)th bus
\( S_n^{grid} \) Short circuit apparent power of the grid (VA)
\( S^L_n \) Load at \( n \)th bus (p.u.)
\( S^{PV-MAX} \) Solar DGs’ rated capacity (kVA)
\( S^{PV-op} \) Solar DGs’ operational capacity (kVA)
\( S^{wind} \) Wind DGs’ total capacity (kVA)
\( S_{L(i,j)} \) Loading of \( l \)th line
\( S_{L(i,j)} \) Loading of line \( l \)
GLOSSARY

$SL_{\text{BASE}}$  Loading of $l$th line without ESS allocation

$SL_{\text{Base}}$  Loading of line $l$ without ESS placement

$SL_{\ell}^{\text{ESS}}$  Loading of $l$th line after ESS allocation

$SL_{\ell}^{\text{ESS}}$  Loading of line $l$ after ESS placement

$SL_{\ell}^{\text{Base}}$  Loading of $l$th line

$SL_{\ell}^{\text{ESS}}$  Loading of line $l$ after ESS allocation

$SL_{\ell}^{\text{ESS}}$  Loading of $l$th line after ESS allocation

$SL_{\ell}^{\text{max}}$  Maximum loading of $l$th line

$SL_{\ell}^{\text{rated}}$  Rated ampacity of $l$th line

$SL_{\ell}^{\text{MAX}}$  Maximum loading limit of $l$th line

$SL_{\ell}^{\text{RATED}}$  Rated ampacity of $l$th line

$SL_{\ell}^{\text{rated}}$  Rated ampacity of line $l$

$SOC_{\text{ESS}}^{k}$  State of charge of $k$th ESS

$SOC_{\text{ESS}}^{x}$  State of charge of $x$th ESS

$SOC_{\text{ESS}}^{\text{g}}$  State of charge of $g$th ESS

$UB1$  Upper limit of decision variable $S_{\ell}^{\text{ESSP}}$

$UB2$  Upper limit of decision variable $S_{n}^{\text{ESSQ}}$

$ub1$  Upper boundary of decision variable $S_{\ell}^{\text{ESS}}$

$ub2$  Upper limit of decision variable $S_{n}^{\text{ESSQ}}$

$UB3$  Upper limit of decision variable $\lambda_{\text{ESS}}^{\ell}$

$ub3$  Upper limit of decision variable $\lambda_{n}^{\text{ESS}}$

$UUC$  Ultrabattery unit cost

$V_{\text{max}}$  Upper limit for bus voltage

$V_{\text{min}}$  Lower limit for bus voltage

$V_{\text{rated}}$  Rated system voltage (p.u.)

$V_{\text{ref}}$  Reference voltage of a bus (p.u.)

$V_{\text{target}}$  Target voltage of the distribution network

$V_{+}$  Positive sequence voltage

$V_{-}$  Negative sequence voltage

$V_{a}$  Average annual wind speed (m/s)

$V_{\ell i}$  Bus voltage of $i$th bus in per unit (p.u.)

$V_{t}$  Voltage magnitude at different times $t$ in a day

$V_{n-t}$  Voltage at times $t$ in a day

$V_{\text{MAX}}$  Upper limit for voltage

$V_{\text{MAX}}$  Upper limit for voltage

$V_{\text{MIN}}$  Lower limit for voltage

$V_{\text{min}}$  Lower voltage limit

$V_{n-t}^{B}$  Voltage at times $t$ in a day

$V_{n}^{B}$  Voltage of $n$th bus (p.u.)

$V_{i}^{+}$  Positive sequence voltage

$V_{i}^{-}$  Negative sequence voltage

$V_{\text{MAX}}$  Upper limit for voltage

$V_{\text{MAX}}$  Upper limit for voltage

$V_{\text{MIN}}$  Lower limit for voltage

$V_{\text{min}}$  Lower voltage limit

$V_{n-t}^{B}$  Voltage at times $t$ in a day

$V_{n}^{B}$  Bus voltage of $n$th bus (p.u.)

$V_{\text{RATED}}$  System’s rated voltage (p.u.)

$V_{\text{rated}}$  Rated voltage of the system in p.u.

$V_{\text{REF}}$  Reference bus voltage (p.u.)

$V_{\text{ref}}$  Reference bus voltage in p.u.

$V_{\text{Target}}$  System’s target voltage

$V_{\text{target}}$  Target voltage of the system

$V_{\text{UFPmax}}$  Maximum VUF

$V_{\text{UFPmax}}$  Maximum VUF

$X_{L}(i,j)$  Reactance of a line linking two adjacent buses, $i$ and $j$

$X_{L}(i,j)$  Reactance of a line connecting two buses, $i$ and $j$

$X_{L}(i,j)$  Reactance of a line linking two buses, $i$ and $j$

$X_{\text{TLoss}}$  Total line loss
GLOSSARY

% $LL_{i}^{base}$ Percent line loading of $i$th line without ESS allocation

% $LL_{i}^{ESS}$ Percent line loading of $i$th line after ESS allocation

% $LL_{i}^{BASE}$ Percent loading of $i$th line without ESS allocation

% $LL_{i}^{ESS}$ Percent loading of $i$th line after ESS allocation

% $LL_{i}^{T_{w-ESS}}$ Total percent loading of a line after ESS allocation

% $LL_{i}^{T_{wo-ESS}}$ Total percent loading of a line without ESS allocation

% $LL_{T}^{w-ESS}$ Total percent line loading of the system after ESS allocation

% $LL_{T}^{wo-ESS}$ Total percent line loading of the system without ESS allocation

% $d_{Sw}$ Percent relative change in bus voltage owing to switching operation of WDGs
Chapter 1

Introduction and Topical Overview

1.1 Introduction

Present distribution networks face a critical period of change driven by various interrelated factors; for example, greenhouse gas (GHG) reduction targets, demand management, power congestion, power quality requirements, integration of renewables, and network expansion and reliability [1–11]. The U.S. Electric Power Research Institute (EPRI) estimated the annual cost of outages to be $100 billion USD, due to disruptions occurring in the distribution system [12]. Energy storage systems (ESSs) are increasingly being embedded in distribution networks to offer technical, economic, and environmental advantages. These advantages include power quality improvement, mitigation of voltage deviation, frequency regulation, load shifting, load levelling and peak shaving, facilitation of renewable energy source (RES) integration, network expansion and overall cost reduction, operating reserves, and GHG reduction [6, 13–20]. As reported in [21–23], ESSs are expected to effectively relieve the problems posed by power oscillations, abrupt load changes, and interruptions of transmission or distribution systems.

Governmental efforts to reduce emissions have forced the power sector to reduce its reliance on conventional fossil fuel-based power generation in favour of renewable energy [24–30], largely in the form of wind and solar [31, 32]. Even though power generation
from renewable energy is more environmentally sustainable, a high reliance on renewable energy can make power distribution systems less reliable [19, 33]. ESSs can support renewable energy by providing voltage support, smoothing their output fluctuations, balancing the power flow in the network, matching supply and demand [18, 21, 34–46], and helping distribution companies (network operators and energy retailers) to meet demand reliably and sustainably. These operational challenges can be mitigated by the appropriate utilization of grid-integrated ESSs [23, 25, 26, 39, 46–49]. Therefore, there is a great potential for using ESSs, from the viewpoint of both utilities and customers.

Research on ESS technologies, development, applications, and benefits is reported in [17–19, 25, 26, 34, 37, 40, 41, 44, 46–48, 50–62]. In [34, 44, 54], several ESS options and their prospects for RES integration and intermittency are discussed. In [37, 41], applications of ESSs for wind energy are studied, while the importance of ESSs for large-scale integration of photovoltaics (PVs) is the focus of [18]. In [25], an ESS, namely, pumped hydro storage (PHS) is used to stable the wind power generation while optimizing the generation mix, total CO2 emissions, and total system costs. [26] investigates the utility-scale application impact of an ESS, e.g., compressed air energy storage (CAES) in a power system scenario considering large RES integration. In [47, 48], short term applications of utility-scale ESSs are presented for mitigating negative operational impacts of a high wind-penetrated power system.

An overview of current and future ESS technologies is presented in [53, 57, 59], while [51] reviews a technological update of ESSs regarding their development, operation, and methods of application. [50] discusses the role of ESSs for various power system operations, e.g., RES-penetrated network operation, load leveling and peak shaving, frequency regulation and damping, low voltage ride-through ability, and power quality improvement. [17] discusses ESS options for some high-power applications, e.g., frequency regulation, voltage control, oscillation damping, and voltage ride-through. [46] presents an economic and technical overview of the role and significance of ESSs and smart grid technologies for future renewable power systems. The policy recommendations and benefits of using ESSs in smart grid are presented in [19] and [52], respectively. Likewise [58] reviews the various ESSs in terms of innovative technologies, energy policies, and regulatory regimes. The potential of ESSs for various services in distribution networks is reviewed in [55, 56], while their operations are discussed in [60]. In [61], research on
1.2 Significance and motivation

ESS allocation is reviewed to provide insights into ESS integration issues and challenges in distribution networks along with guidelines for future ESS-related research. In [62], optimal ESS planning is discussed, including optimal ESS locations, energy capacity, and power rating determination in distribution networks.

Although various investigations on ESS options and application benefits have been carried out in the literature listed above, there is still scope for performance improvement of power networks through ESS utilization. However, more emphasis is required on optimal placement and sizing of utility-scale ESSs in order to mitigate the issues of power networks. For instance, utility-scale ESSs can be employed for minimizing voltage deviation, real and reactive power losses, line loading, flickers, frequency deviation, and rate of change of frequency (ROCOF) and thereby performance, power quality, and frequency response of power networks can be improved.

1.2 Significance and motivation

Asset management of distribution networks is an essential task of network service providers to ensure safe and secure operation of networks. However, the fulfilment of this target can increase the overall network cost. This cost could comprise network reinforcement for voltage and thermal stability which can significantly affect electricity prices. Voltage profile improvement and flicker disturbance minimization are also crucial for maintaining network power quality. On the other hand, the frequency regulation issue is considered as a key concern by the transmission system operator in order to ensure safe and reliable operation of networks.

As discussed in the preceding section, the deployment of utility-scale energy storage systems (ESSs) is a significant avenue for maximizing the energy efficiency of a power network, and overall network performance can be enhanced by their optimal placement, sizing, and operation. An optimally sized and placed ESS can facilitate peak energy demand fulfilment, enhance the benefits from the integration of renewables and distributed energy sources, minimize power losses and line loading, improve voltage profile, aid power quality management, improve frequency response, and reduce overall network operational costs. Recently, the deployment of ESSs to improve frequency response has
1. INTRODUCTION AND TOPICAL OVERVIEW

attracted the attention of both academia and industry [63], [64]. Unfortunately, misusing or mislocating ESSs in distribution networks can degrade power quality and reduce reliability as well as load control while also affecting voltage and frequency regulation. Therefore, the motivations of this study are to provide distribution system operators with a low cost solution for better asset management practice as well as maintaining power quality, and to improve frequency response of transmission networks. More specifically, the key drive of the proposed research is to develop effective strategies regarding optimal allocation and sizing of utility-scale ESSs, and thereby solve various network issues relating to both transmission and distribution levels.

1.3 Aims of the thesis

The aims of this research are:

(a) Optimal placement and sizing of distributed ESSs to improve performance of distribution networks using P injection approach.

(b) Application of PQ injection approach for optimal ESS allocation and sizing and achieving further improvements of distribution network performances compared to P-injection approach.

(c) Optimal placement and sizing of distributed ESSs to improve performance and power quality of distribution networks.

(d) Optimal sizing of a grid-scale ESS to improve frequency response of transmission networks.

1.4 Thesis contributions

The contributions of this thesis arise from analyzing the existing barriers in integrating utility-scale ESSs and consequently developing new strategies to alleviate these barriers. The novelty of this research is summarized below:
1.4 Thesis contributions

- This research develops a generic model of utility-scale ESSs and selects an ESS technology (Ultrabattery) based on unit ESS cost. This research also employs a dynamic ESS model (developed by PowerFactory) for frequency response analysis and performs necessary tuning according to system requirements.

- This research proposes several important strategies for placement and sizing of distributed ESSs in both transmission and distribution levels. This uses the IEEE-33 bus and IEEE-39 bus systems for studying the impact of ESS integration in distribution and transmission networks, respectively. Two types of renewables such as solar and wind are incorporated and performance analysis is conducted. The ESS sizing is performed in two different phases: (a) using a uniform ESS size throughout the network and (b) using non-uniform ESS sizes throughout the network. Furthermore, the impact of ESS placement and sizing is analyzed through the application of P injection and PQ injection approaches and performance comparison is presented.

- For distribution networks, this research minimizes some important problems such as voltage deviation, real and reactive power losses, and line loading as performance parameters. Furthermore, it minimizes the network flickers (both continuous and switching) along with network performance parameters and thereby improves the performance and power quality of distribution networks.

- Regarding transmission networks, this research analyzes the impact of battery ESS (BESS) sizing to improve frequency response by performing dynamic simulation study (conducting generator and load trip events) under peak and off-peak load scenarios. The problem formulation includes minimization of frequency deviation and ROCOF. As the BESS provides necessary active power to the network for frequency support, the tuning of active power part of PQ controller is required. Hence, the tuning of parameters $K_p$ and $T_{ip}$ of PQ controller (active power part) is performed during optimization. Furthermore, a sensitivity analysis is performed for ESS allocation in transmission networks based on minimum line loading.

- Several performance indices are defined mathematically such as indices for voltage deviation, voltage profile improvement, real, reactive, and total power losses, line loading, continuous, switching, and total flickers, relative voltage change during
switching operations of wind turbines, and power quality improvement to evaluate the network performance and power quality. Furthermore, the performance improvement using the developed approaches is reported.

- For optimization, this research employs three optimization approaches including the artificial bee colony (ABC), a hybrid optimization approach namely fitness-scaled chaotic artificial bee colony (FSCABC), and particle swarm optimization (PSO) algorithms. The ABC algorithm is used as a main approach for first investigation, while the FSCABC is applied as a key technique for latter investigations. Moreover, the ABC and PSO algorithms are employed to compare the obtained results from main optimization approach (FSCABC or ABC).

1.5 Thesis outline

This thesis is organized in nine chapters as follows:

- Chapter 1 introduces the research overview, including research significance and motivation, aims of the thesis, and contributions of the thesis in the relevant fields. This chapter also presents ideas on the research visions and expected outcomes in terms of placement and sizing of grid-scale ESSs using various approaches.

- Chapter 2 provides an inclusive overview of ESSs by reviewing the relevant literature. This chapter describes the functions of a grid-scale ESS, effective storage stratagem, ESS selection criteria regarding the applications in distribution networks, a detailed comparison of various ESS technologies, and smart charging-discharging procedures of ESSs.

- Chapter 3 provides a comprehensive review of the relevant and recent literature regarding ESS placement, sizing, operation, and power quality. This chapter critically analyzes the literature on various topics such as tools for system analysis, various power quality issues with mitigation scopes, and optimization approaches. This chapter also discusses the challenges for ESS development and placement, ESS contributions in relation to energy security and society, and presents key findings for future research scopes. Finally, this chapter presents the research questions targeted by this PhD project.
Chapter 4 presents a strategy for ESS placement and sizing to improve performance of distribution networks. Three important performance parameters including the minimization of voltage deviation, power losses, and line loading are considered and included in the problem. The ESSs only inject P to the network and the sizing is accomplished in two different categories: (a) with a uniform ESS-size and (b) with non-uniform ESS sizes. Two types of renewables such as solar and wind are integrated to the network. The artificial bee colony (ABC) algorithm is used as main optimization approach and the obtained results are compared with another well-known optimization approach namely particle swarm optimization (PSO). This chapter also measures the performance improvements through some performance indices.

Chapter 5 investigates the same problem as conducted in Chapter 4 using PQ injection approach and improves the distribution network performance further compared to P injection approach. The study of this chapter applies a hybrid optimization approach namely fitness-scaled chaotic artificial bee colony (FSCABC) and compares the obtained results with ABC optimization approach. This chapter also presents the performance improvement of distribution networks (using PQ injection approach) in percentage.

Chapter 6 demonstrates an optimal ESS placement and sizing strategy to improve distribution network performance and power quality. Minimization of network flickers is incorporated in the objective function along with other performance parameters addressed in Chapter 4 and Chapter 5. In other words the objective function simultaneously minimizes voltage deviation, line losses and loading, and flickers of a distribution network. Two types of renewables such as solar and wind are integrated to the network where the flickers (both continuous and switching) are injected by wind turbines. The study of this chapter also employs FSCABC hybrid optimization approach and compares the obtained results with ABC optimization approach.

Chapter 7 covers an optimal sizing strategy for a grid-scale ESS to improve frequency response of transmission networks. The objective function includes minimization of frequency deviation as well as ROCOF. A sensitivity analysis is performed for placing the grid-scale ESS to the network. Two types of network events
1. INTRODUCTION AND TOPICAL OVERVIEW

such as generator outage and load trip events are performed for frequency response analysis during peak and off-peak load periods. The FSCABC approach is applied for optimization and the obtained results are compared through the application of PSO algorithm. This chapter also covers the ESS sizing in terms of both power and energy ratings.

- Chapter 8 presents a general discussion regarding the results presented in each chapter. This chapter also relates the research questions that are addressed by the overall PhD project.

- Chapter 9 summarizes the concluding remarks of all chapters and provides suggestions for future research directions.
Chapter 1 references


CHAPTER 1 REFERENCES


Chapter 2

Overview of Energy Storage Systems in Power Networks

This chapter provides a comprehensive review of energy storage systems (ESSs) from a distribution network perspective, including ESS benchmarks, ESS technologies and selection, and ESS charging-discharging rules.¹

2.1 Energy storage systems

For distribution networks, an ESS converts electrical energy from a power network, via an external interface, into a form that can be stored and converted back to electrical energy when needed [1–3]. The electrical interface is provided by a power conversion system and is a crucial element of ESSs in distribution networks [4, 5]. Fig. 2.1 [6] is a conceptual diagram of a grid-connected ESS, including internal and external configurations. ESSs are usually equipped with essential management and control components that underpin safe and reliable operation of storage facilities. The objective is not only to facilitate local management but also to have coordinated control over other components during grid-scale applications. The power electronics components of the grid-connected

¹This presented chapter is a part of the following published paper: Choton K. Das, Octavian Bass, Ganesh Kothapalli, Thair S. Mahmoud, Daryoush Habibi, "Overview of energy storage systems in distribution networks: Placement, sizing, operation, and power quality" Renewable and Sustainable Energy Reviews, Vol-91, pp.12051230, 2018.
2. OVERVIEW OF ENERGY STORAGE SYSTEMS IN POWER NETWORKS

ESSs modulate the waveforms of voltage and current as needed to or from the grid. A storage controller and converter manage ESS operations, define the active and reactive power set-points (P and Q) for the ESS and provide intelligent decision-making. Depending on the design, the P and Q set-points for a certain ESS application can be controlled locally or remotely. The “Energy Storage Medium” corresponds to any energy storage technology, including the energy conversion subsystem. For instance, a Battery Energy Storage Medium, as illustrated in Fig. 2.1, consists of batteries and a battery management system (BMS) which monitors and controls the charging and discharging processes of battery cells or modules. Thus, the ESS can be safeguarded and safe operation ensured over its lifetime. However, large-scale ESSs require a BMS hierarchy which involves a master control module to coordinate the charging and discharging of the slave control modules.

Figure 2.1: Conceptual diagram of an ESS
2.2 Effective storage stratagem

The ESS can store energy to produce electricity and discharge it, depending on the demand or cost benefits [1, 7]. Benchmarks for an effective ESS include [8]:

(i) Dispatchability – responsiveness to electricity demand fluctuations that may occur on various cycles (daily, weekly, and seasonal) due to variations in domestic and industrial loads and changes in some environmental factors, e.g., weather conditions.

(ii) Interruptibility – reactivity to the intermittency of renewable energy supplies such as wind and solar, the seasonally alternating behaviours of hydropower and biomass, and the recurring instabilities associated with fossil-fuel supplies.

(iii) Efficiency – the capacity to recover and reuse energy that is otherwise wasted.

2.3 Selection of an ESS for distribution networks

The history of ESSs began in the early 20th century with the use of lead-acid battery as an ESS to provide power for residual loads on a DC electricity network [3, 9, 10]. Since then ESS technologies have continued to develop and they are increasingly being used for power system applications such as grid stabilization, load shifting, grid operational support, power quality improvement, and reliability management [9, 11]. Additionally, the increasing grid integration of intermittent renewable distributed generation (DG) significantly change the scenario of distribution network operations. These operational challenges are mitigated by ESS incorporation, which plays a vital role in improving the overall network’s stability and reliability [9, 12]. The ESSs could also perform an important role in deregulated markets, e.g., providing arbitrage and increasing the value of RESs [12].

With the focus shifting to making these functions a reality, governments worldwide (e.g., EU, U.S., and Japan) encourage the development and deployment of ESSs through nationally supported programmes [9, 10]. Consequently, ESSs are frequently used in large-scale applications such as power generation, distribution and transmission networks, distributed energy resources, renewable energy, and local industrial and commercial facilities [10]. The application of ESSs to distribution networks can benefit the
2. OVERVIEW OF ENERGY STORAGE SYSTEMS IN POWER NETWORKS

Figure 2.2: Different types of ESS technologies for distribution networks

supply company, the customer, and the distribution network operator (DNO) as well as the transmission system operator (TSO) and the generation operator (conventional and DG) in numerous ways [13]. In [14], ESS opportunities for stakeholders in the electricity value chain are analyzed from the viewpoints of the French distribution system and island networks. The Sandia National Laboratory reports on ESS application benefits in the U.S. by evaluating the cost-benefit of distribution and transmission network upgrade deferral arbitrage and generation capacity credit, and power quality issues [15–17]. An electricity grid can use numerous energy storage technologies as shown in Fig. 2.2, which are generally categorized in six groups: electrical, mechanical, electrochemical, thermochemical, chemical, and thermal. Depending on the energy storage and delivery characteristics, an ESS can serve many roles in an electricity market [4].

As placement of large-scale ESSs involves substantial investment, selecting ESSs appropriately on the basis of performance expectations is challenging. The current level of adoption and the technical specifications of different ESS technologies are assessed
### Table 2.1: Comparison of technical characteristics of different types of ESSs along with environmental impact issues

<table>
<thead>
<tr>
<th>ESS Technology</th>
<th>Available Capacity (MW)</th>
<th>Maturity</th>
<th>Efficiency (%)</th>
<th>Response Time</th>
<th>Lifetimes, Years (cycles)</th>
<th>Power Capital Cost ($/kW)</th>
<th>Energy Capital Cost ($/kWh)</th>
<th>Charge Time</th>
<th>Discharge Time</th>
<th>Environmental Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Electrical</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capacitor</td>
<td>Commercialized</td>
<td>0–0.05</td>
<td>60–65</td>
<td>ms</td>
<td>~ 5 (&gt; 50,000)</td>
<td>200–400</td>
<td>500–1000</td>
<td>s–hr</td>
<td>ms–60</td>
<td>Small</td>
</tr>
<tr>
<td>Supercapacitor</td>
<td>Developing</td>
<td>0–0.3</td>
<td>90–95</td>
<td>8 ms</td>
<td>20+ (&gt;100,000)</td>
<td>100–450</td>
<td>300–2000</td>
<td>s–hr</td>
<td>ms–60</td>
<td>None</td>
</tr>
<tr>
<td>SMES</td>
<td>Developing</td>
<td>0.1–1</td>
<td>95–98</td>
<td>&lt;100 ms</td>
<td>20+ (&gt;100,000)</td>
<td>200–489</td>
<td>1000–72,000</td>
<td>min–hr</td>
<td>ms–8 sec</td>
<td>Moderate</td>
</tr>
<tr>
<td>(2) Mechanical</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PHS</td>
<td>Mature</td>
<td>100–5000</td>
<td>75–85</td>
<td>s–min</td>
<td>40–60 (&gt;13,000)</td>
<td>2000–4300</td>
<td>5–1000 hr–months</td>
<td>1–24 hr+</td>
<td>Large (–ve)</td>
<td></td>
</tr>
<tr>
<td>CAES</td>
<td>Mature</td>
<td>5–1000</td>
<td>70–89</td>
<td>1–15 min</td>
<td>20–40 (&gt;13,000)</td>
<td>400–1000</td>
<td>2–120 hr–months</td>
<td>1–24 hr+</td>
<td>Large (–ve)</td>
<td></td>
</tr>
<tr>
<td>(Large-scale)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FES</td>
<td>Early commercialized</td>
<td>0.1–20</td>
<td>93–95</td>
<td>&lt;4 ms–s</td>
<td>15+ (&gt;100,000)</td>
<td>250–350</td>
<td>1000–14,000</td>
<td>s–min</td>
<td>ms–15</td>
<td>Almost none</td>
</tr>
<tr>
<td>(3) Electrochemical</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lead-acid</td>
<td>Mature</td>
<td>0–40</td>
<td>70–90</td>
<td>5–10 ms</td>
<td>3–15 (2000)</td>
<td>300–600</td>
<td>200–400 min–days</td>
<td>s–hr</td>
<td>Moderate</td>
<td></td>
</tr>
<tr>
<td>UltraBattery</td>
<td>Developing</td>
<td>0–36</td>
<td>5–15</td>
<td>ms</td>
<td>3–15 (3000)</td>
<td>–</td>
<td>200 min–days</td>
<td>s–hr</td>
<td>Moderate</td>
<td></td>
</tr>
<tr>
<td>NaN</td>
<td>Commercialized</td>
<td>0.05–34</td>
<td>80–90</td>
<td>1 ms</td>
<td>10–15 (2500–4500)</td>
<td>1000–3000</td>
<td>300–500 s–hr</td>
<td>s–hr</td>
<td>Moderate</td>
<td></td>
</tr>
<tr>
<td>Li-ion</td>
<td>Demonstration</td>
<td>0–100</td>
<td>85–90</td>
<td>20 ms–s</td>
<td>5–15</td>
<td>900–4000</td>
<td>600–3800 min–days</td>
<td>min–hr</td>
<td>Moderate</td>
<td></td>
</tr>
<tr>
<td>NiCd</td>
<td>Commercialized</td>
<td>0–40</td>
<td>60–65</td>
<td>ms</td>
<td>1000–20,000</td>
<td>10–20 (2000–3500)</td>
<td>500–1500</td>
<td>400–2400 min–days</td>
<td>s–hr</td>
<td>Moderate</td>
</tr>
<tr>
<td>Metal-air</td>
<td>Developing</td>
<td>0–0.01</td>
<td>50</td>
<td>5 ms</td>
<td>(100–300)</td>
<td>100–250</td>
<td>10–60 hr–months</td>
<td>s–24 hr+</td>
<td>Small</td>
<td></td>
</tr>
<tr>
<td>VRB</td>
<td>Early commercialized</td>
<td>0.03–3</td>
<td>85</td>
<td>1 ms</td>
<td>5–10 (12,000+)</td>
<td>600–1500</td>
<td>150–1000</td>
<td>s–10 hr</td>
<td>Moderate</td>
<td></td>
</tr>
<tr>
<td>ZnBr</td>
<td>Demonstration</td>
<td>0.05–10</td>
<td>75</td>
<td>5–10 (2000+)</td>
<td>700–2500</td>
<td>150–1000 hr–months</td>
<td>s–10 hr</td>
<td>Moderate</td>
<td>(–ve)</td>
<td></td>
</tr>
<tr>
<td>(4) Thermochemical</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Solar fuel</td>
<td>Developing</td>
<td>0–10</td>
<td>20–30, planned</td>
<td>–</td>
<td>(~)</td>
<td>(~)</td>
<td>(~)</td>
<td>(~)</td>
<td>(~)</td>
<td>(~)</td>
</tr>
<tr>
<td>(5) Chemical</td>
<td>Research/development</td>
<td>0–58.8</td>
<td>25–58</td>
<td>1s</td>
<td>5–20+</td>
<td>500–10,000</td>
<td>15 hr–months</td>
<td>sec–24</td>
<td>Small</td>
<td></td>
</tr>
<tr>
<td>H2 Fuel Cell</td>
<td>developed/marketed</td>
<td>(1000–20,000)</td>
<td>5–1000</td>
<td>–</td>
<td>20–40 (&gt;13,000)</td>
<td>200–300</td>
<td>3–30 min–days</td>
<td>1–8 hr</td>
<td>Benign (+ve)</td>
<td></td>
</tr>
<tr>
<td>(6) Thermal</td>
<td>CES</td>
<td>0.1–300</td>
<td>–</td>
<td>10–20</td>
<td>(~)</td>
<td>5–15 (&gt;13,000)</td>
<td>(~)</td>
<td>(~)</td>
<td>(~)</td>
<td>(~)</td>
</tr>
<tr>
<td>AL-TES</td>
<td>Developing</td>
<td>0–5</td>
<td>50–90</td>
<td>20–50</td>
<td>10–20 (~)</td>
<td>500–10,000</td>
<td>15 hr–months</td>
<td>1–8 hr</td>
<td>Small</td>
<td></td>
</tr>
<tr>
<td>HT-TES</td>
<td>Developed</td>
<td>0–60</td>
<td>30–60</td>
<td>5–15 (~)</td>
<td>30–60</td>
<td>min–months</td>
<td>1–24 hr+</td>
<td>Small</td>
<td>(–ve)</td>
<td></td>
</tr>
</tbody>
</table>

MW = Megawatt, kW = Kilowatt, kWh = Kilowatt hour, eff. = Efficiency, ms = Milliseconds, min = Minutes, s = Seconds, hr = Hours, –ve = Negative, +ve = Positive
Table 2.2: Relative advantages, disadvantages and applications of various ESSs

<table>
<thead>
<tr>
<th>ESS Technology</th>
<th>Advantages</th>
<th>Disadvantages</th>
<th>Applications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electrical</td>
<td>Fast response, higher cycle life</td>
<td>Lower capacity, lifetime, and efficiency</td>
<td>Power quality, Energy management, Load leveling, Black start</td>
</tr>
<tr>
<td>Superconducting Magnetic Energy Storage (SMES)</td>
<td>High power and efficiency, long lifetime, and potential of 2000+ MW capacity</td>
<td>Impact to health for large-scale sites</td>
<td>Emergency back-up, Time shifting, Load leveling, Black start, RES integration, RE back-up, Peak shaving, Load leveling, Black start, RES integration, RE back-up, Peak shaving</td>
</tr>
<tr>
<td>Mechanical</td>
<td>Higher capacity and lower cost/unit capacity</td>
<td>Disturbance to local wildlife and water level</td>
<td>PH (Large-scale), CAES</td>
</tr>
<tr>
<td>Electrochemical</td>
<td>Lower capital cost</td>
<td>Lower energy density</td>
<td>Lead-acid, UltraBattery, NaS, Li-ion, NiCd, Metal-air, VRB, ZnBr</td>
</tr>
<tr>
<td>Thermochemical</td>
<td>High energy density and specific energy, environmentally viable, almost zero self discharge</td>
<td>Lower efficiency</td>
<td>Solar thermal, High temperature thermal energy storage (HT-TES)</td>
</tr>
<tr>
<td>Chemical</td>
<td>Almost zero self discharge, long term storage, variety of cell types for various applications</td>
<td>Frequently requires expensive catalyst</td>
<td>Hydrogen fuel cell</td>
</tr>
</tbody>
</table>
2.3 Selection of an ESS for distribution networks

from technical viewpoints in [10, 18–22]. The ESS inclusion options for increasing RES penetration at a utility level are explored in [11] by comparing their technical characteristics, cost, and environmental impact. Importantly, in [12, 18, 19, 23, 24], different ESS technologies are considered based on current state of development, available methods, technology updates, and application potential. Most specifically, in [12, 19], different ESS technologies are compared by reviewing various studies which highlight their applications rather than specifying their advantages and disadvantages. Technical comparisons of different ESSs, including their advantages and disadvantages, are provided in [23], although other factors such as capacity, lifetime, charge and discharge times, environmental impact, and various aspects of their application are not considered. More comprehensive comparisons of various ESS technologies for distribution networks are provided in Table 2.1 [1, 10–12, 18, 19, 23, 25–28] and Table 2.2 [12, 18, 19, 23, 25, 26].

Table 2.1 classifies various ESS technologies as electrical, mechanical, electrochemical, chemical, and thermal. These technologies are considered in regard to ESS capacity, maturity, efficiency, response time, lifetime and cycles, power and energy capital cost, time for charging and discharging, and environmental impact. The advantages, disadvantages, and applications of various ESS technologies are provided in Table 2.2, where the ESS applications are considered as proven, promising or possible for each key application. According to Table 2.1, two of the ESSs in the electrical category, supercapacitor and SMES, have a higher efficiency rating than any other ESS technologies, and also have lower costs and a lifetime exceeding 20 years. All of the electrical ESSs are used for power quality issues, while the SMES is also an option for RES integration and network stabilization as indicated in Table 2.2. The supercapacitor is a promising option for voltage regulation, network stabilization, and end-user applications, while SMES is suitable for voltage regulation, spinning reserve, and end-user services. For the mechanical category, although the mature ESSs (PHS and CAES) are more efficient and have a longer lifetime than other ESS options, their power cost is higher. In contrast, the cost of energy for PHS and CAES is lower due to the high discharge time, although the opposite is true for FES. Both mechanical ESSs are used for many network applications such as energy management, peak shaving, time shifting, and load leveling.
2. OVERVIEW OF ENERGY STORAGE SYSTEMS IN POWER NETWORKS

Another mechanical option, FES, which is in the early phase of commercialization, has good efficiency, long lifetime (above 15 years) and low power cost and is used for power quality improvement, RES integration, and emergency back-up. Although batteries (electrochemical ESSs) are proven options for most distribution network applications and have long lifetime and good efficiency, some options (e.g., NaS, Li-ion, NiCd, VRB, and ZnBr) are costly. The emerging ESS technologies such as solar fuel (thermochemical ESS) and CES (thermal ESS) have low environmental impacts, while the environmental impact of some other technologies, e.g., PHS, CAES, and batteries, is adverse. Another developing ESS technology in the chemical category, the H₂ Fuel Cell, has almost zero self-discharge and long-term storage capacity as well as being a promising option for most distribution network applications. Despite having some advantages – e.g., lower cost and higher lifetime – and being proven options for energy management applications, the thermal ESSs have slow response times. However, they are promising options for other applications such as peak shaving, time shifting, load levelling, black start, seasonal storage, and network expansion.

The appropriate selection of grid-scale ESSs depends on various factors such as system capacity, required performance, ESS cost and reliability, and type of application. As can be seen from Tables 2.1 and 2.2, with a higher efficiency and a longer lifetime, the SMES is a proven option for power quality maintenance, RES integration, and network stabilization, and a promising option for spinning reserve, voltage regulation, and end-user services. In contrast, the thermochemical, chemical, and thermal ESSs are promising storage technologies with potential for different grid-scale applications. Despite some limitations, batteries are well-established ESSs for most of the applications in Table 2.2. A recent version, the UltraBattery (also known as advanced lead-acid battery), developed by the Furukawa Battery Co. of Japan and the Commonwealth Scientific and Industrial Research Organization (CSIRO) of Australia and tested by the U.S. Advanced Lead-Acid Battery Consortium (ALABC), is frequently incorporated in grid-scale applications in the U.S. and Australia as it performs better than other electrochemical ESSs (e.g., lead-acid) [25, 29]. The accumulation of lead sulfate is a well-known barrier to lead-acid batteries attaining the sustained level of operation required for heavy duty performance: this problem is reduced by incorporating carbon in the UltraBattery. This battery acts as a buffer to tackle the high-rate charge/discharge process by inserting
2.4 Smart charging-discharging of ESSs

a supercapacitor so that the ESS can operate successfully within a state of charge (SoC) window below 70%, unlike conventional lead-acid batteries [25, 30].

Thus, the optimal choice of ESSs depends on the expected performances, ESS characteristics and application types (as presented in Table 2.1 and 2.2); however, there must be some trade-offs among different ESS facilities. Despite having lower energy density, the FES, which is in an early commercialization phase, may be the optimal choice for a distribution network as it offers many advantages such as a low power capital cost, high power and efficiency ratings, fast response, a lifetime exceeding 15 years, and a fast charging time. Moreover, it has no negative environmental impacts and is already used with some important distribution network applications such as power quality improvement, RES integration, and emergency back-up. It is also a promising option for energy management, spinning reserve, network stabilization, voltage regulation, and end-user applications.

2.4 Smart charging-discharging of ESSs

ESSs need smart charging and discharging protocols to eliminate some problems, e.g., excessive charging or discharging and power compensation failures, even if their energy capacities are unlimited. Control of the SoC of ESSs in distribution network applications is essential. An SoC control strategy is proposed in [31] to facilitate localized control, regulate the SoC of each ESS, exploit available ESS capacities effectively and ensure voltage regulation while evading ESS saturation or depletion for various operational conditions. Appropriate charging and discharging strategies, and adherence to manufacturers’ recommendations must be maintained to address the major challenges of ESS deployments, i.e. achieving maximum output, optimal efficiency, and a long lifetime.

Several recent studies have continued to develop suitable charging and discharging protocols for ESSs. An optimal charging and discharging schedule of an ESS is presented in [32] to facilitate peak load shaving in a grid-connected PV system. For the proposed ESS model in Fig. 2.3, the charging and discharging rules are expressed in Eq. 2.1 and Eq. 2.2 [33]. This model and charging and discharging strategies are useful for
integrating RESs (wind) into the grid and mitigating the intermittency of wind energy and line congestion [33].

Charging strategy:

\[
P_{n}^{IN} = \min \left\{ \left( F_{n}^{L} - C_{RL} \right), P_{n}^{IN}_{ESS}, \frac{(E_{MAX} - E_{n-1})}{\Delta t} \right\} \quad (2.1)
\]

When line congestion appears \((F_{n}^{L} - C_{RL} > 0)\) with the charge rate restricted by the \(P_{n}^{IN}_{ESS}\) as well as by the ESS availability, only the ESS will be charged.

Discharging strategy:

\[
P_{n}^{OUT} = \min \left\{ \left( C_{RL} - F_{n}^{L} \right), P_{n}^{OUT}_{ESS}, \frac{(E_{n-1} - E_{MIN})}{\Delta t} \right\} \quad (2.2)
\]

When there is no congestion \((F_{n}^{L} - C_{RL} < 0)\) and the discharge rate is restricted by the \(P_{n}^{OUT}_{ESS}\) as well as by the available line capacity \((C_{RL} - F_{n}^{L})\), to avoid new congestion.
2.4 Smart charging-discharging of ESSs

because of discharged power, then only discharging of ESSs will occur. The discharging
of ESSs continues on the condition that stored energy is available.

Importantly, in [34], an ESS charging-discharging strategy for low-voltage distribu-
tion networks is proposed to mitigate abrupt fluctuations in PV outputs and support
peak loads in the evening. In that research, the current SoC status of the ESS and the
probable length of charging/discharging periods are considered for effective use of avail-
able ESS capacity. With the proposed strategy, the deviation of the SoC of ESSs can also
be tracked and adjusted to the desired level. Again, an optimal ESS charging-discharging
schedule is developed on an hourly basis to minimize the distribution system’s energy
losses and mitigate the intermittency of PV-based DG outputs [35]. The optimization is
accomplished by using the genetic algorithm (GA) and the proposed method has great
potential for analysis of future ESS applications such as voltage support, peak-load
shifting, regulation service, and reliability improvement.

In [36], a real-time, distributed algorithm for an aggregator, coordinating a group
of distributed ESSs, is presented to provide a power balancing service to a power grid
through charging or discharging. In this research, a modified Lyapunov optimization
framework for real-time power balancing is developed by incorporating some character-
istics such as time-varying power imbalance and electricity price, finite battery size con-
straints, cost of using external energy sources, and battery degradation. The proposed
algorithm asymptotically provides optimal performance as the capacity of distributed
ESSs increases with quick convergence. However, this research does not deal with the
joint optimization of self-charging and power balancing, which may be a challenging
problem. In [37], a three-phase unbalanced distribution optimal power flow optimization
model is developed for optimal operation scheduling of ESSs in distribution networks
with RES integration and load fluctuations. In this model, optimal charge/discharge
schedules of ESSs are generated while satisfying voltage limits; simulation results reveal
reductions in power losses and mitigation of peak demand, i.e. improvement of overall
efficiency in the distribution network. However, there is no evaluation of the proposed
method on a larger system and in meshed networks.

A new framework – flexible distribution of energy and storage resources – is devel-
oped in [38–40], which is inspired by the V-shape formations of flocks of birds [41, 42]
and the peloton/echelon formations of cycling racing teams [43–45]. In the case of V-
shape formations, the birds or cyclists change their positions continuously to save energy,
otherwise the leading bird or cyclist becomes exhausted sooner than its drafting coun-
terparts. By using these concepts, intelligent charging and discharging protocols are
developed in that framework to save ESS energy and lifetime. However, this frame-
work is only developed for micro-grids by considering the distance to a placed ESS as a
controlling factor and not extended to distribution grids.

The uncontrolled charging and discharging affect the cycle life of ESSs and are respon-
sible for the capacity fade phenomenon known as ESS ageing caused with the decrease
of ESSs’ deliverable capacity [46, 47]. Generally, the cycle life of an ESS indicates the
number of cycling times with allowable capacity fading of lower than 80% of its nominal
value [48, 49]. The results of applying the flexible distribution of energy and storage
resources approach in [40] show that ESS lifetime depends on the cycling sequence, pat-
tern, and occurrence and can be extended by 76% of the baseline (which is 86% in an
ideal case). As ESSs are expensive devices for distribution network applications, ESS
lifetime extension is a critical issue. Smart charging and discharging strategies can save
energy, facilitate optimal ESS efficiency achievement, and ensure a longer lifetime.

2.5 Conclusions

This chapter has provided a comprehensive overview of ESSs in power networks. It
has also presented some key ideas for the optimal choice of ESSs and the smart charging
and discharging of ESSs. Although there are various types of ESSs with extensive
advantages and disadvantages, the optimal choice of ESS will depend on the expected
performance enhancements, ESS characteristics, and application types. While batteries
are widely used ESSs in various applications, the detailed comparative analysis of ESS
technical characteristics conducted in this research suggest that FES also warrants more
consideration, in terms of benefits, in some distribution network scenarios. The smart
charging and discharging of ESSs are both crucial for saving energy, achieving optimum
ESS efficiency, increasing ESS lifetime and achieving cost-effective network operation.
Further research on the application of smart charging and discharging algorithms for
optimal ESS implementation is recommended.
Chapter 2 references


CHAPTER 2 REFERENCES


Chapter 3

Literature Review, Research Focus, and Methodologies

In this chapter, optimal ESS sizing, placement, and operation are reviewed thoroughly (based on the recent literature) and critically analyzed by highlighting the strategies that are used, advantages, and the scope of future research. In addition, this chapter presents a comprehensive review on the following topics:\footnote{This presented chapter is a part of the following published paper: Choton K. Das, Octavian Bass, Ganesh Kothapalli, Thair S. Mahmoud, Daryoush Habibi, \textit{"Overview of energy storage systems in distribution networks: Placement, sizing, operation, and power quality"} Renewable and Sustainable Energy Reviews, Vol-91, pp.12051230, 2018.}

- This chapter discusses about tools and their suitability for system modeling, simulation, and analysis, considering ESS applications in power networks.
- The chapter discusses various issues related to the power quality of distribution networks and their mitigation scopes with ESSs.
- The chapter verifies the importance of hybrid meta-heuristic optimization approaches for obtaining optimal solutions, rather than other optimization techniques.
- The chapter identifies the challenges for ESS development and placement and discusses the ESS contributions to energy security and society.
The chapter presents several key findings which will benefit researchers by highlighting potentially important directions for future research.

3.1 Optimal placement, sizing, and operation of ESSs, and power quality issues in distribution networks

3.1.1 Determining optimal ESS locations

The ESS is a particularly important device that will increasingly become available to network operators and planners. There are many ESS options to be explored in terms of technical characteristics and application benefits for the distribution network, as tabulated in Table 2.1 and 2.2. The large capital investment required makes the adoption of an ESS a significant step for a network, and their installation must therefore be part of an extensive smartening of distribution networks [1]. To maximize the benefits from an ESS operation, it is crucial to determine the optimal ESS locations in a distribution network. Alongside the technical benefits of ESS usage such as improved voltage and power quality, utility system reliability, reduced power losses, and relieved distribution congestion [1–5], the use of ESSs in non-optimal locations can lead to reduced network performance [6].

Although an ESS can be installed anywhere in a distribution system, appropriate placement can facilitate optimal ESS operation for power quality improvement, peak demand mitigation, overall network cost reduction, RES integration, and system effectiveness. The determination of optimal ESS locations in a distribution network can involve one or more optimization problems depending on the benefits targeted. To facilitate this determination process, a comprehensive survey is indispensable. Various types of distribution system data should be collected for a particular distribution network prior to analysis with a powerful decision-making tool. Appropriate tools could include DIgSILENT PowerFactory, MATLAB, Gurobi, Powerworld, CYME, GridLAB-D, OpenDSS, PSCAD, ISM-DEW (integrated system model- distributed engineering workstation), and EMTP-RV (the electromagnetic transient program- restructured version). The DIgSILENT PowerFactory provides useful solutions for distribution network problems including system design, data handling, modeling and optimization capabilities,
3. LITERATURE REVIEW, RESEARCH FOCUS, AND METHODOLOGIES

and grid interactions skill in a multi-user environment [7]. The suitability of DIgSI-
LENT PowerFactory has been demonstrated in several relevant studies [8–17], where
it has been utilized on its own and also in tandem with other tools such as MATLAB.
MATLAB is also a widely used tool for distribution network analyzes such as power-flow
analysis with a high DG penetration [18], fault analysis [19], development of a new algo-
rithm (for customer classification) and load profiling technique [20], optimal grid sizing
and control with ESSs [21], and optimal placement, sizing and operation of ESSs [22–25].
For simulation packages in MATLAB, MATPOWER offers solutions for complex optimal
power flow (OPF) problems for both large-scale AC and DC [26], while PSAT provides
scope for designing and analyzing distribution networks [27]. Moreover, the flexibility
of MATLAB is apparent from its capacity for integration with other software such as
DIgSILENT PowerFactory [12, 13, 15–17], Gurobi [28, 29], OpenDSS [30–32], PSCAD
[33], ISM-DEW [32], and GridLAB-D [34]. Gurobi is also used for various ESS applica-
tions in distribution networks such as ESS allocation, scheduling, operation, and control
[28, 29, 35]. PSCAD can be employed for power system analysis, dynamic distribution
network modeling, and RES modeling [33, 36, 37].

Similarly, other software can also be used to deal with distribution network problems.
Powerworld is used for power flow analysis [38] and the optimal placement and sizing
of DG [39]. The CYMDIST (Cooper Power Systems distribution simulator), a part
of CYME software, is suggested in [32, 40] for planning, modeling, and simulating a
distribution network. GridLAB-D, OpenDSS, ISM-DEW, and EMTP-RV are also used
[30–32, 41–46] for the analysis of various problems in distribution networks as well as
smart grids. Thus, a specific tool should be selected depending on the distribution
network challenges. This can be employed for analysis independently or together with
other software.

3.1.2 Optimal ESS sizing

Because of the crucial role played by the ESSs, their sizing is essential for guar-
anteeing the correct operation of distribution grids. From both economic and security
viewpoints, an accurate and practical ESS model would enhance modeling of system
operation [58, 59]. Optimally sizing the ESS involves finding the optimal ESS power
Table 3.1: Review of literature based on optimal sizing and strategies of ESSs

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Grid Scenario</th>
<th>Sizing strategies</th>
<th>ESS types</th>
<th>Advantages</th>
<th>Research scopes</th>
</tr>
</thead>
<tbody>
<tr>
<td>[47]</td>
<td>A wind farm-ESS system</td>
<td>Non-dominated sorting genetic algorithm II (NSGA-II)</td>
<td>Lead-acid</td>
<td>Good cycle control, improvement of ESS lifetime,</td>
<td>Incorporation of other ESSs, e.g., UltraBattery, and performance evaluation and comparison; applying other hybrid optimization approaches</td>
</tr>
<tr>
<td>[48]</td>
<td>A wind-ESS based hybrid power system</td>
<td>Auto regression moving average (ARMA) modeling technique, sequential monte carlo simulation (MCS), MSAES based on the Fischer-Burmeister algorithm</td>
<td>NiCd and Li-ion</td>
<td>Providing flexibility to decision makers for optimal ESS sizing under different values of load shifting or reliability levels</td>
<td>The geographical constraints for ESS sizing are not considered, cost functions can be developed for other ESS technologies with different optimization techniques</td>
</tr>
<tr>
<td>[49]</td>
<td>A distribution network</td>
<td>Multi-period AC optimal power flow (OPF) and bi-level AC OPF iterative processes</td>
<td>Not specified</td>
<td>Reduction of curtailment from RESs; management of congestion and voltages</td>
<td>Hybrid RES consideration, performance investigation of different types of ESSs considering effects of charging discharging cycles, technical parameters, and lifetime</td>
</tr>
<tr>
<td>[50]</td>
<td>-</td>
<td>Pareto-optimal sizing</td>
<td>Hybrid ESS-batteries and SCap</td>
<td>Applicable to solar power and self usage, stable performance, can be converted to LP with reduced computation time</td>
<td>Other ESS involvement for hybridization, applying other optimization approaches</td>
</tr>
<tr>
<td>[51]</td>
<td>A distribution grid</td>
<td>GAMS modeling language and CPLEX solver</td>
<td>Technology neutral but based on lead-acid and Li-ion</td>
<td>Time shifting and arbitrage, energy related CAPEX reduction, benchmark for aggregator profitability</td>
<td>Analysis can be done for power applications, incentive mechanism design ensuring cost-effectiveness of photovoltaic (PV) use and distribution grid design</td>
</tr>
<tr>
<td>[52]</td>
<td>A modified General Electric Distribution System</td>
<td>New energy management system, MATLAB simulation</td>
<td>Li-ion phosphate</td>
<td>Developing cost-benefit ESS size with high PV penetration, facilitating peak load shaving, voltage regulation and peaking generation</td>
<td>Can be applied to other distribution systems (large-scale), the approach can be employed to determine ESS cost-benefit size for other applications such as spinning reserve, frequency regulations.</td>
</tr>
</tbody>
</table>
3. LITERATURE REVIEW, RESEARCH FOCUS, AND METHODOLOGIES

Grids

A distribution Grid Modelled in GAMS, simple branch and bound (SBB) solver VR and NaS Maximizing the difference between the discharging and charging costs of an ESS; minimization of investment cost Cost functions can be developed for other ESS technologies, application of other algorithms and strategies

A medium voltage smart grid A new cost-based optimization strategy, SQP-based inner algorithm Redox batteries (VR) Facilitating RES integration, deferring network upgrading and offering VAR regulation Option for multi-objective optimization considering different technical and economic objectives of ESSs, DG penetration, and deployment of ESSs and capacitors

Large/small-scale grids with PV generation Markov-chain-based ESS model Decreasing system cost, ensuring adequate power availability, tracking the energy state of PV-ESS environment Can be applied for wind power plants, development of a real-time availability estimator with real-time SoC or energy level

Large-scale wind farm in utility grid Application of four strategies - simple, fuzzy, simple ANN, and advanced ANN with a comparison ZnBr Increase in output predictability of wind power plant, decrease in wind integration cost Other sizing topologies may be selected and compared with advanced ANN, analysis can be focused on PV or hybrid RES integration

Stand-alone PV systems weakly connected to grid Particle swarm optimization (PSO) Lead-acid, Ni-Cd, and H₂ Storage chain Minimization of total levelized cost, achievement of cost benefits for ESS uses in both short term and mid term Other optimization approaches can be applied, research can be conducted with other ESS technologies

Ref. = Reference, MSAES = Modified self-adaptive evolutionary solver, SCap = Supercapacitors, LP = Linear programming, GAMS = General algebraic modeling system, CPLEX = Simplex method as implemented in the C programming language, SQP = Sequential quadratic programming, LP = Linear programming, ESS = Electrical energy storage, ESS = Energy storage system, DG = Distributed generation, ANN = Artificial neural network, VAR = A unit of reactive power.
and energy capacities in order to minimize the operating cost of the distribution grid while still meeting performance targets. The capital cost of ESSs is an important part of calculating the distribution grid’s operating cost which in turn depends on the payback period of the investment, so the lifetime of ESSs is crucial. The number of cycles and the SoC at which the ESS operates are the two main factors that affect the lifetime of batteries [60]. The estimated lifetime of an ESS is used to calculate the cost associated with the ESS in [22], whereas in [60, 61] lifetime is determined according to prediction models. Table 3.1 classifies the research on optimal ESS sizing from the viewpoints of grid scenario, applied strategies of sizing, ESS technologies used, advantages, and research scope. Most of these studies [47, 48, 52–57] consider a specific ESS technology for sizing, while a few [49, 51] are ESS technology neutral. The main research focus is to minimize cost, integrate RESs and analyze their effects, and achieve network benefits. However, there is also some scope for future research, as identified in Table 3.1.

After determining the optimal locations of ESSs in distribution networks, the next step should be optimal ESS sizing. This should be established for a distribution grid, as large ESSs impose higher investment and maintenance costs on the grid while small ESSs may not provide the desired economic benefits and flexibility or meet predefined reliability objectives for the grid. The optimal ESS sizing for a distribution network should comprise all costs directly related to network benefits. For instance, if RESs are integrated into the distribution networks, it is necessary to include fixed operation and maintenance costs for integrated RESs in ESS sizing. Moreover, selecting an ESS for optimal sizing and comparing it with alternative ESSs in terms of cost and performance can help to identify an appropriate ESS option for a location in a distribution network.

3.1.3 Literature review on ESS placement and operation

In this section, the existing research on ESS placement and operation problems is classified from the viewpoints of grid scenario, objectives to be fulfilled, algorithm and strategies used, testing bus and, various advantages and limitations. In addition, the section details whether individual pieces of research work specify ESS technology or not. Table 3.2 summarizes the relevant literature on ESS placement and operation problems (as placement and operation are interrelated) from various viewpoints, based on different
techniques, scenarios, and limitations. The optimal placement and operation of an ESS can help to adjust the power flow and reduce power loss in distribution networks. This is particularly useful for balancing generation with consumption and maintaining system stability [62].

From the perspective of targeted objectives, most of the literature [6, 22–25, 63–85] focuses on finding optimum ESS locations in a distribution network, while optimal operation is targeted by [22, 23, 35, 77–79, 86–95]. Optimal ESS scheduling is accomplished in [96] to improve voltage profile and minimize network losses and cost (in terms of energy). The optimal ESS placement embedded with network reconfiguration is carried out by [28, 97, 98], where the power flow is optimized [97], network security and losses are further minimized [28], and RES integration is maximized [98]. However, more optimal reconfiguration of distribution networks can be introduced for better network performance expectations. For optimization, different types of algorithms e.g., dynamic programming, GA, particle swarm optimization (PSO), fuzzy PSO, are employed; however, no comparisons of such heuristic methods are presented in the literature except [70] (which is not a comprehensive comparison), and hybrids of these algorithms are reported in only a few publications [23, 70, 72, 73, 80, 84, 87]. Software such as MATLAB, PSLF, OpenDSS, CPLEX, GAMS, Gurobi, and DIgSILENT PowerFactory is used for system simulation and modeling, although MATLAB is the major choice. Many researchers use a specific test bus system such as IEEE 13, 14, 15, 24, 30, 33, 34, 37, 39, 84, 119, 123, 906, or 8500 to verify system performance instead of general test systems. From the ESS technology viewpoint, batteries (single or hybrid) are widely used among other ESS options and the comparative investigation of various ESS types is presented in [23, 25, 66, 67, 70, 81–83, 86, 90] to provide better outcomes for large-scale capital investment in distribution networks.

Notably, to ensure sustainable energy supply with RES integration, wind is considered in [23, 67, 69, 72, 79–82, 84, 93–95], PV is integrated in [6, 22, 24, 28, 29, 76, 77, 83, 86–88, 92, 96, 100], and both (or generic RESs ) are also incorporated in some studies, e.g., [35, 64, 66, 68, 87, 97, 98]. Though generation from RESs significantly affects power quality due to intermittent nature, overall mitigation of this issue is not considered in the RES integrated distribution network by the literature in Table 3.2. Some power issues such as voltage fluctuations or deviations, frequency deviations,
Table 3.2: Review of literature based on optimal placement and operation of ESSs

<table>
<thead>
<tr>
<th>Literature (chronological)</th>
<th>Grid Scenario</th>
<th>Targeted Objectives</th>
<th>Applied Algorithm and Strategies</th>
<th>Test bus</th>
<th>ESS types</th>
<th>Advantages</th>
<th>Limitations/future research opportunities</th>
</tr>
</thead>
<tbody>
<tr>
<td>[28]</td>
<td>Active distribution networks</td>
<td>Optimal allocation of distributed ESSs and grid reconfiguration</td>
<td>Convex optimal power flow (OPF), Gurobi and MATLAB interface- YALMIP used for implementation</td>
<td>6-bus and 70-bus</td>
<td>Not specified</td>
<td>Minimization of voltage deviation, line congestion, energy supply and ESS investment costs, and network losses</td>
<td>Only photovoltaic (PV) is considered as an RES, and more optimal grid reconfiguration is also possible</td>
</tr>
<tr>
<td>[77]</td>
<td>Active distribution grids</td>
<td>ESS operation and planning using a non-parametric chance-constrained (NPCC) optimization approach</td>
<td>Mixed integer linear programming (MILP), Gaussian approximations, Monte Carlo simulation (MCS), NPCC, scenario based optimization</td>
<td>Radial 12-bus, IEEE 13</td>
<td>Li-ion</td>
<td>Modeling of electric vehicles (EVs) and DG uncertainties, ESS operation and installation costs minimization</td>
<td>Generalization of the proposed method for current chance-constraints is not investigated, the slack bus voltage is considered as fixed which fluctuates practically; this approach can be applied to other non-ESS scenarios, addressing the inaccuracy of line current chance and ESS energy constraints</td>
</tr>
<tr>
<td>[97]</td>
<td>Soft open point based distribution networks</td>
<td>Optimal determination of distributed ESS locations and energy/power capacities including network reconfiguration and DG reactive power capability</td>
<td>MISOCP, implemented in MATLAB interface- YALMIP (modified)</td>
<td>IEEE 33</td>
<td>Not specified</td>
<td>Improved utilization of RES generation, reduction of network losses, providing supports to decision makers for optimal ESS sizing and placement</td>
<td>Power quality issues due to RES integration are not addressed, investigation can be done with more optimal network reconfiguration</td>
</tr>
<tr>
<td>[63]</td>
<td>Distribution networks</td>
<td>Optimal ESS placement and sizing</td>
<td>Analytical modeling, OPF, and DistFlow modeling</td>
<td>IEEE 123 (modified)</td>
<td>Not specified</td>
<td>Energy loss minimization</td>
<td>More mathematical proof of radial networks, development of more realistic models, investigations on more complicated spatial structure of background injections at buses</td>
</tr>
</tbody>
</table>
3. LITERATURE REVIEW, RESEARCH FOCUS, AND METHODOLOGIES

**LV Distribution Grids**

- **Modeling and optimal operation of distributed ESSs**
  - Multi-period AC-OPF, linearized AC-OPF, model predictive control (MPC), MLIP, and CPLEX
  - Li-ion for two technologies: Li-CoO2 and LiFePO4
  - 30% reduction of ESS losses, real time control of ESSs, minimization of ESS degradation, and maximization of PV utilization

- **Power quality issues** can be investigated with other ESS types.

**Distribution Networks**

- Multi-objective energy management with ESSs
  - Hybrid of grey wolf optimizer and PSO, pareto-optimal and fuzzy decision making strategies, MATLAB

- IEEE 84 Batteries
  - Operational cost reduction and reliability improvement

- RES uncertainties are not considered, performance indices other than reliability can be addressed.

**LV Radial Networks**

- Optimal allocation of ESSs (ESS number, locations, and sizes)
  - Multi-period OPF, clustering and sensitivity analysis (CSA), CVX modeling toolbox, and SeDuMi solver
  - IEEE 34 (modified), Italian 17-bus, 200 random networks

- Prevention of under and overvoltages, minimization of total network costs (ESS costs and network losses)

**Appropriate ESS control algorithms** can be investigated for real-time network operation.

**Distribution Networks**

- Optimal DG allocation and ESS integration
  - Loss sensitivity factor approach, multi-objective ant lion optimizer, grey relation projection theory, chance-constrained programming, and probabilistic power flow

- PG & E 69-bus

- Improvement of renewable DG output, minimization of line losses, maximization of investment benefits and voltage stability

- Investigation with more focus on optimal distributed ESS allocation can be carried out, RES and load uncertainty consideration, hybrid ESSs incorporation.

**Active Distribution Networks**

- Decentralized real-time control of distribution networks using ESSs
  - Multi-agent system (MAS), clustered real-time model based control, MATLAB, and YALMIP optimizer

- IEEE 13 Li-Titanate

- Good voltage support and line congestion management, feasible voltage and current profiles

- Optimal distributed ESS allocation with larger number of buses can be investigated.

**Distribution Systems**

- Optimal ESS deployment and network reconfiguration
  - Stochastic MILP
  - IEEE 119

- Overall network cost minimization, voltage profile improvement, system loss minimization

- Frequency regulation, flicker mitigation, and other power quality issues can be addressed.

**Optimal DG allocation and ESS integration** can be performed in real-time network operation can be addressed. Appropriate ESS control algorithms can be investigated with other ESS types.

**Optimal ESS deployment** can be performed in real-time network operation can be addressed. Appropriate ESS control algorithms can be investigated with other ESS types.

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**Optimal DG allocation and ESS integration** can be performed in real-time network operation can be addressed. Appropriate ESS control algorithms can be investigated with other ESS types.
<table>
<thead>
<tr>
<th>[66] Distribution systems</th>
<th>Optimal allocation of ESSs</th>
<th>A game-theoretic multi-agent approach</th>
<th>IEEE 15 (radial)</th>
<th>Lead-acid, and Li-ion</th>
<th>Interaction between ESSs, achievement of Nash equilibrium, improvement and risk mitigation of energy transaction mechanism for energy agents</th>
<th>Other distribution network performance indices, e.g., voltage profile and power quality improvement are not investigated</th>
</tr>
</thead>
<tbody>
<tr>
<td>[100] A distribution system</td>
<td>Development of controller for grid connected distributed ESSs' real-time operation.</td>
<td>Markov chain process for system modeling and MCS using SimPower toolbox of MATLAB</td>
<td>Canadian urban benchmark system</td>
<td>Not specified</td>
<td>stochastic stability of distributed ESSs</td>
<td>Only PV is considered as a RES and if wind is considered then flicker issue can be investigated</td>
</tr>
<tr>
<td>[35] Active distribution systems</td>
<td>Scheduling and operation of mobile ESSs</td>
<td>PSO, energy management system, MISOC, Gurobi</td>
<td>41-bus (radial)</td>
<td>Batteries</td>
<td>Cost minimization of imported grid power and profit maximization of network operator, voltage supports</td>
<td>Power quality issues can be investigated for mobile ESSs, application of hybrid meta heuristic optimization approach</td>
</tr>
<tr>
<td>[67] Distribution networks</td>
<td>Optimal ESS allocation</td>
<td>GA combined with linear-programming (LP) solver, and a sequential MCS</td>
<td>33-bus (radial)</td>
<td>Lead-acid, VR, and NaS</td>
<td>Cost reduction regarding ESS installation, maintenance, interruption, system upgrade costs, and energy losses</td>
<td>Power quality issues mitigation and distribution system reliability improvement are not investigated</td>
</tr>
<tr>
<td>[101] A modified 4 area power system</td>
<td>Coordinated control of a grid-connected battery ESS operated with a wind power plant</td>
<td>A coordinated control strategy implemented in FESTIV, PSLF dynamic simulation software, and MATLAB/Simulink SimPowerSystems</td>
<td>18-bus</td>
<td>Li-ion</td>
<td>Multi-scale frequency support</td>
<td>Other power quality issues such as flicker, voltage deviation, overvoltage, and undervoltage can be investigated</td>
</tr>
<tr>
<td>[68] European LV distribution networks</td>
<td>Optimal allocation and sizing of ESS considering RESs</td>
<td>Non-dominated sorting genetic algorithm II (NSGA-II)</td>
<td>IEEE 906</td>
<td>Batteries</td>
<td>Voltage profile improvement, DG and ESS costs reduction, ESS lifetime maximization</td>
<td>Overall power quality improvement is not investigated</td>
</tr>
<tr>
<td>[75] Active distribution networks</td>
<td>Optimal allocation, sizing, and operation of large-scale ESSs in RES penetrated scenarios.</td>
<td>Dynamic programming optimization algorithm and a mathematical framework</td>
<td>13-bus</td>
<td>VRB</td>
<td>Maximizing RES consumption and ESS benefits, optimizing ESS costs</td>
<td>Voltage profile and power quality investigation can be carried out</td>
</tr>
</tbody>
</table>
### 3. LITERATURE REVIEW, RESEARCH FOCUS, AND METHODOLOGIES

<table>
<thead>
<tr>
<th>Topic</th>
<th>Methodologies</th>
</tr>
</thead>
<tbody>
<tr>
<td>PV-enhanced distribution networks</td>
<td>Steady-state operation of ESSs, ESS charging-discharging strategy with the incorporation of a load factor, developed in OpenDSS and DIgSILENT PowerFactory. IEEE 37 Batteries Reduction of peak load and quantification of power generation and voltage intermittency. A more adaptive control strategy can be employed, energy management systems, and the communication link between ESSs and PVs can be analyzed.</td>
</tr>
<tr>
<td>Distribution networks</td>
<td>Optimal ESSs integration (ESS number, sizes, and locations) using NSGA-II and Pareto dominance concept. 94-bus (radial) Network reliability improvement (i.e., SAIDI and MAIFI), equipment cost minimization. Modeling of specific ESS types is not presented, other reliability indices, e.g., SAIFI, CAIFI, ASIFI, ASAI, CTAIDI, and CAIDI are not addressed.</td>
</tr>
<tr>
<td>A Distribution grid with high RES penetration</td>
<td>Control of ESSs to track power, MPC using MATLAB and Gurobi. Controlling and smoothing of net power profile exchanged with the grid. A more theoretical assessment of RES imbalance impact on the control system performance and field testing works can be accomplished.</td>
</tr>
<tr>
<td>Distribution systems</td>
<td>Sizing and siting of ESSs using GA, LP, and OpenDSS IEEE 8500 Batteries Peak demand minimization, voltage fluctuation mitigation. Application of other optimization approach, Specific ESS technology is not addressed, and modelled, power quality issues are not investigated.</td>
</tr>
<tr>
<td>Multiple ESSs planning (location, size, and operational characteristics) using cost benefit analysis</td>
<td>Optimal power factor approach, load following control method, and GA toolbox in MATLAB. 33-bus (radial) Not specified. Maximization of total NPV, improvement of load factors and voltage profiles. More investigations for power quality improvement using other optimization approach can be targeted.</td>
</tr>
<tr>
<td>Smart grid</td>
<td>Optimal ESS operation addressing real-time pricing. Integer coded GA, Auto regression moving average (ARMA) modeling technique, MATLAB. Lead-acid Minimization of daily net costs. Optimization parameters other than real time pricing can be addressed and analyzed.</td>
</tr>
<tr>
<td>Wind penetrated power systems</td>
<td>Optimal ESSs' allocation based on sensitivity analysis. Multi-period AC OPF, MATLAB. IEEE 14 and IEEE 118 Not specified. Minimization of cost, power losses and wind power curtailment, maximization of line congestion mitigation and system benefits. Power quality issues are not investigated.</td>
</tr>
<tr>
<td>Reference</td>
<td>Network Type</td>
</tr>
<tr>
<td>-----------</td>
<td>----------------------------------</td>
</tr>
<tr>
<td>[72]</td>
<td>A tap-changer equipped distribution network</td>
</tr>
<tr>
<td>[102]</td>
<td>A power distribution system</td>
</tr>
<tr>
<td>[70]</td>
<td>Distribution networks</td>
</tr>
<tr>
<td>[103]</td>
<td>LV radial distribution networks</td>
</tr>
<tr>
<td>[104]</td>
<td>A Korean distribution system</td>
</tr>
<tr>
<td>[96]</td>
<td>European medium voltage (MV) distribution network</td>
</tr>
</tbody>
</table>
3. LITERATURE REVIEW, RESEARCH FOCUS, AND METHODOLOGIES

An active distribution network
Optimal ESS planning (location, capacity, and power rating)
PEM, Hybrid TS-PSO approach, OPF, probabilistic load flow
21-bus ZnBr Overall cost minimization including ESS, O&M, reliability and constraints violation costs, peak shaving, better voltage regulation, and enhanced reliability
The proposed approach can be applied to the real sized systems using some other modification strategies, e.g., sensitivity analysis

Distribution grids
Effects of ESS inclusion on grid efficiency
Dynamic programing optimization - UltraBattery, lead acid with CEE, VR, Li-ion, and CAES
Loss reduction in distribution grid, economically beneficial
Power quality issues after the placement and RES integrated ESS placement are not considered

A power network
Optimal placement and control of ESSs
Mathematical modeling with deep analysis - Not specified
Minimizing generation costs
Fixed installment costs are neglected during optimization and ESS applications to renewable generation at faster time-scales are not studied.

An IEEE benchmark radial distribution system
Determining optimum ESS location and size, and optimal ESS operation with wind integration
MISOCP model combining unit commitment and AC-OPF, MATLAB toolbox - YALMIP used for implementation
IEEE 34 Not specified
Spinning reserve supports for variable wind power, peak demand mitigation
Power quality issues are not addressed

Smart grid with grid-scale ESSs
Characterization of optimal value-lifetime performance pair for ESSs
Constrained stochastic shortest path (CSSP), Pareto optimal approach - Battery Balancing the economic value and lifetime of ESS, energy arbitrage application of ESSs under dynamic pricing
Although, the analysis is done for four types of batteries, the ESS types are not specified

IEEE 118 Smart grid model - Implementation and performance of ESS applications, demonstration of economic wind energy storage, and grid code compliance for ESS operation
IEEE 118 Smart grid model - Implementation and performance of ESS applications, demonstration of economic wind energy storage, and grid code compliance for ESS operation
IEEE 118 Smart grid model - Implementation and performance of ESS applications, demonstration of economic wind energy storage, and grid code compliance for ESS operation
3.1 Optimal placement, sizing, and operation of ESSs, and power quality issues in distribution networks
# 3. LITERATURE REVIEW, RESEARCH FOCUS, AND METHODOLOGIES

<table>
<thead>
<tr>
<th>Reference</th>
<th>Methodology</th>
<th>Objective</th>
<th>Technology Used</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>[83]</td>
<td>Distribution systems</td>
<td>Optimal ESS allocation and determination of loads to be shed, network reliability improvement</td>
<td>GA combined with linear-programming solver, sequential MCS</td>
<td>33-bus (radial) Lead acid, CAS, NaS, VR</td>
</tr>
<tr>
<td>[84]</td>
<td>Wind is the only RES considered as DG</td>
<td>Minimization of interruption cost and improvement of distribution system reliability, annual cost reduction</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[85]</td>
<td>A power grid</td>
<td>Optimal ESS operation and picking out the optimal energy and reserve bids for ESSs considering Intermittent nature of RESs to market prices</td>
<td>Optimal bidding mechanism, two tractable design approaches</td>
<td>IEEE 24 Li-ion</td>
</tr>
<tr>
<td>[86]</td>
<td>Wind is the only RES considered as DG</td>
<td>Ensuring the profitability of ESS investment</td>
<td>For RES generation, only wind is considered; the suitability of other ESS technologies is not analyzed</td>
<td></td>
</tr>
<tr>
<td>[87]</td>
<td>A radial distribution network</td>
<td>Optimal allocation of ESS to mitigate risk for distribution companies (DISCOs)</td>
<td>Fuzzy PSO (FPSO) and a cost-benefit analysis method</td>
<td>IEEE 15 Li-ion and lead-acid</td>
</tr>
<tr>
<td>[88]</td>
<td>A deregulated power system with high wind penetration</td>
<td>Optimal placement of ESS to minimize cost</td>
<td>Market-based probabilistic OPF, GA, an energy arbitrage model</td>
<td>IEEE 24 CAES Maximum utilization of wind power, minimization of hourly social cost</td>
</tr>
<tr>
<td>[89]</td>
<td>A distribution network</td>
<td>Optimal ESS allocation to distribution companies (DISCOs) to maximize the plant profit through the planning (policy) to operation (for wind energy time shifting) policy</td>
<td>Stochastic dynamic programming framework, inhomogeneous Markov model, objective function approximation, MCS, CPLEX</td>
<td></td>
</tr>
<tr>
<td>[90]</td>
<td>A grid-connected wind power plant</td>
<td>Adaptation of optimal ESS operation (for wind energy time shifting) policy to maximize the plant profit</td>
<td>Stochastic dynamic programming framework, inhomogeneous Markov model, objective function approximation, MCS, CPLEX</td>
<td>CAES Considerably higher profit compared to fixed policy</td>
</tr>
<tr>
<td>[91]</td>
<td>A deregulated power system with high wind penetration</td>
<td>Optimal allocation of ESS to distribution companies (DISCOs)</td>
<td>Market-based probabilistic OPF, GA, an energy arbitrage model</td>
<td>IEEE 24 CAES Maximum utilization of wind power, minimization of hourly social cost</td>
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<tr>
<td>[92]</td>
<td>A distribution network</td>
<td>Optimal ESS allocation to distribution companies (DISCOs) to maximize the plant profit through the planning (policy) to operation (for wind energy time shifting) policy</td>
<td>Stochastic dynamic programming framework, inhomogeneous Markov model, objective function approximation, MCS, CPLEX</td>
<td></td>
</tr>
<tr>
<td>[93]</td>
<td>A grid-connected wind power plant</td>
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</tr>
<tr>
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<td>Stochastic dynamic programming framework, inhomogeneous Markov model, objective function approximation, MCS, CPLEX</td>
<td></td>
</tr>
<tr>
<td>[95]</td>
<td>A distribution network</td>
<td>Optimal ESS allocation to distribution companies (DISCOs) to maximize the plant profit through the planning (policy) to operation (for wind energy time shifting) policy</td>
<td>Stochastic dynamic programming framework, inhomogeneous Markov model, objective function approximation, MCS, CPLEX</td>
<td></td>
</tr>
</tbody>
</table>

[42]
3.1 Optimal placement, sizing, and operation of ESSs, and power quality issues in distribution networks

<table>
<thead>
<tr>
<th>Reference</th>
<th>Distribution Network</th>
<th>Optimal and flexible ESS operation to maximize the profit compared to fixed ESS operation</th>
<th>A two stage framework- (1) optimization of integer variables (2) active-reactive OPF problem, MATLAB, GAMS</th>
<th>41-bus rural network</th>
<th>Battery</th>
<th>Achievement of higher profit than fixed ESS operation, price reduction</th>
<th>More than one ESS cycling is not allowed, only wind is considered as RES, ESS types are not specified</th>
</tr>
</thead>
<tbody>
<tr>
<td>[95]</td>
<td>A distribution network</td>
<td>To minimize the cost by introducing standby ESSs</td>
<td>PSO, DIgSILENT, PowerFactory</td>
<td>Battery and fuel cell</td>
<td>Cost efficiency</td>
<td>Impacts of grid configuration, load priority, load growth, and cost of optimum placement are not studied</td>
<td></td>
</tr>
<tr>
<td>[85]</td>
<td>A distribution network</td>
<td>Optimal ESS allocation to maximize the benefits for the utility and DG owner</td>
<td>ARMA modeling technique, MATLAB, IEEE-RTS</td>
<td>Lead-acid, VRLA, NaS, ZnBr, and VRB</td>
<td>Minimization of annual electricity cost</td>
<td>Not all possible ESS benefits for the utility (e.g., peak shaving, reliability enhancement) are considered</td>
<td></td>
</tr>
</tbody>
</table>

**Technologies and Methods:**

- FESTIV = Flexible energy scheduling tool for integrating variable generation
- PSLF = General electric's positive sequence load flow
- O&M = Operation and maintenance
- PSO = Particle swarm optimization
- MISOCP = Mixed integer second order cone programming
- CVX = Matlab-based modeling system for convex optimization
- SeDuMi = A linear/quadratic/semidefinite solver for Matlab and Octave
- RBTS = Roy Billinton test system
- GA = Genetic algorithm
- DE = Differential evaluation
- DG = Distributed generation
- CEE = Carbon-enhanced electrode
- VRLA = Valve-regulated lead-acid
- AC-OPF = AC optimal power flow
- RTS = Reliability test system
- GAMS = General algebraic modeling system
- CPLEX = Simplex method as implemented in the C programming language
overvoltage, and undervoltage are addressed in some studies [22, 28, 64, 65, 68, 71–
73, 76, 80, 96, 98, 99, 101, 103, 104]. However, there are still opportunities for in-depth
studies addressing other power quality issues such as flicker, harmonic distortion, voltage
sag, voltage swell, short or long term interruption, and oscillatory transients. Moreover,
the impact on the lifetime of ESSs, after optimal placement and operation, is addressed
by very few research works [6, 22, 68, 83, 86, 91].

To have sustainable solutions for the optimal ESS placement problem in an RES in-
tegrated distribution network, various network issues, including the uncertainties of RES
generation and loads, must be considered and modelled. However, these uncertainties
have only been taken into account in a few studies [23, 24, 28, 29, 64, 66, 69, 70, 72,
73, 76, 77, 80, 82, 84, 94, 95]. In [80, 84, 94], the uncertainty of wind generation has
been considered and modelled by different techniques. In [80], the uncertainty of wind
generation is considered for the formulation of cost probability optimization problem and
discretized by the 5-point estimation method (5PEM), while the 2PEM is employed by
[84]. Wind uncertainty, along with price uncertainty, is handled by a stochastic dynamic
programming technique in [94]. In contrast, the load demand uncertainty in [23, 82]
is presumed to follow the hourly IEEE-reliability test system load-shape rather than
being characterized by special techniques; however, the researchers employ a probabilis-
tic approach to deal with the load and DG stochastic behaviours. In [95], the wind
power and load demand uncertainties are considered by assuming they can be forecast
in a time-frame optimization, while in [73] these are modelled using PEM. However, the
inaccuracies of these forecasts are neglected in that literature. The uncertainties of a
hybrid system (solar PV and wind) and load demand are addressed in [24] by consid-
ering different scenarios of PV, wind, and loads. A special method (K-means method)
is used for data clustering, thereby reducing the number of stochastic input scenarios.
Similarly, the RES and load uncertainties are also taken into account in several studies
[28, 29, 64, 66, 69, 70, 72, 77] and modelled using different techniques. Though the
above studies deal with uncertainties of RES generation and/or loads, the optimization
problem formulation for addressing these types of uncertainties is vitally important for
future research of optimal ESS placement and operation.

The control of ESSs using different algorithms or approaches is very important for op-
timal ESS operation. Some control approaches are employed in [29, 99–101, 103, 104]. In
3.1 Optimal placement, sizing, and operation of ESSs, and power quality issues in distribution networks

ESS operations are facilitated through the coordination-based control method to provide voltage and frequency support. In [29], model predictive control (MPC) is applied to ESS operations for the power tracking and shaving of the distribution network. A stochastic stability enhancement strategy is employed in [100] for stable ESS operations. Furthermore, in [99], the real-time control of an active distribution network is accomplished through a multi-agent-system (MAS)-based decentralized control of ESSs. Besides these ESS control techniques, as discussed above and in Table 3.2, more control strategies can be employed to facilitate the optimal ESS operations in distribution networks.

Some studies introduce the mobile ESS concept which is also interesting from the ESS application viewpoint [35, 102]. In [35], some important distribution network objectives – such as profit maximization for the network operator, cost minimization for imported grid power and voltage support – are achieved through mobile ESS scheduling and operation. Again, in [102], distribution system reliability is improved with mobile ESS deployment and operation. The optimal placement, scheduling, operation and control of mobile ESSs can be investigated by applying different techniques in distribution networks.

Various types of performance and reliability indices for distribution networks are investigated in Table 3.2. In [74], distribution network reliability through ESS integration is investigated by addressing the indices momentary average interruption frequency index (MAIFI) and system average interruption duration index (SAIDI), while skipping other indices such as system average interruption frequency index (SAIFI), customer average interruption duration index (CAIDI), customer total average interruption duration index (CTAIDI), customer average interruption frequency index (CAIFI), average service availability index (ASAI), average system interruption frequency index (ASIF), average system interruption duration index (ASIDI), customers experiencing multiple interruptions index (CEMIn), and customers experiencing long interruption durations index (CELID) [105]. On the other hand, in [72], network reliability is improved through optimal probabilistic-based ESS allocation, where the reliability indices are not considered. However, all of the reliability indices, including SAIDI, SAIFI, CAIDI, CTAIDI, CAIFI, MAIFI, ASIFI, ASAI, ASIDI, CEMIn, and CELID are important for overall reliability analysis of distribution networks using ESSs and should be considered. The
steady state characteristics of distribution networks are optimized in almost all relevant
studies listed in Table 3.2, but transient or dynamic issues are neglected for optimal
ESS placement and operation problems except [100] where the transient stability of ESS
grid-tied inverter is only focused.

The charging impacts of electric vehicles (EVs) on distribution networks are also

The charging impacts of electric vehicles (EVs) on distribution networks are also
crucial. EV is a promising technology for the reduction of GHG emissions and the al-
leviation of climate change and global warming concerns [106–110]. With the targets
for carbon emission reductions, governments of many countries are adopting EVs rather
than conventional vehicles [106, 108, 110]. Furthermore, the potential contributions of
EVs can facilitate continually increasing generation from intermittent RESs, e.g, wind
[109, 110]. Consequently, EVs are becoming more popular as sustainable transporta-
tion systems and are undergoing rapid development [106, 108]. The increasing charging
pattern of EVs has a considerable impact on distribution networks [106–108, 111], in-
cluding impacts on load profile, voltage profile, system components, power losses, phase
unbalance, grid reliability and harmonics, as well as power quality. Hence, optimal ESS
placement and operation should consider the charging impact of EVs on a distribution
network. In [77], EV charging stations and EV uncertainty are considered in optimal
ESS planning in an active distribution network. The PEM is utilized in [72], another
research on optimal ESS planning in distribution networks, to address the uncertainty
of EVs. However, more research should be carried out in relation to optimal ESS place-
ment and operation by considering various EV integration impacts, EV uncertainty, EV
charging and discharging, and other optimization parameters.

The optimal placement and operation of ESSs are very important for maximizing
network benefits. To obtain solutions for the optimal ESS placement and operation
problems, various factors related to network performance and reliability should be con-
sidered. Identifying the optimal solution for ESS placement in a power system directly
depends on the case studies (including system size and topology). This concept is ev-
dent in [22], where the optimum locations of ESSs are determined through simulation
for two case studies, a low voltage (LV) distribution network in Western Australia and a
medium voltage (MV) IEEE 33 bus system. Depending on the system size, the required
number of ESSs to be installed in a network can be determined, which may satisfy the
3.1 Optimal placement, sizing, and operation of ESSs, and power quality issues in distribution networks

objective function of the problem. Take for example a micro-grid, which is a small section of a power system or distribution network. One ESS may be enough to mitigate system demand or power quality problems. However, for a large power system such as a distribution network, several ESSs may be required. In addition, the ESSs should be distributed in the network rather than centralized to provide more opportunities for problem mitigation and greater flexibility. For instance, analyzing and comparing the applicability of distributed ESSs with a centralized ESS through simulation in [84] reveal that the distributed ESSs are more efficient. Again, the idea is validated in two case studies of [80] where the capacities of 42.3 MW and 29.2 MW are met by optimal placement of four and three ESSs respectively (with different capacities) at different buses. Although much research has been undertaken on these issues, comprehensive ESS models covering placement, operation, and sizing in a distribution network are needed for different case studies and scenarios.

As the mitigation of power quality problems is linked with optimal ESS placement, the next section discusses the ability of ESSs to mitigate various power quality problems and the importance of optimal ESS placement in distribution networks.

3.1.4 Power quality problems and the role of ESSs

Power quality refers to the measurement, analysis, and improvement of the bus voltage for maintaining a sinusoidal waveform at rated voltage and frequency, which is generally meant to express the quality of voltage and/or current [112]. The power quality of distribution networks may be affected by various issues as listed in Table 3.3 [3, 112–130], which can affect the performance of sensitive loads and equipment. The steadiness of power demand, particularly for large companies or bulk tariff consumers and highly automated industries, can be affected by a network’s power quality degradation. Therefore, power quality improvement in a distribution network is an important issue from the customer viewpoint [131].

Fig. 3.1 represents the most common voltage quality problems according to the IEEE 1159-1995 standard [130] for two durations: short (<1 min) and long (>1 min); where r.m.s variations (for short durations) are divided into three time intervals- instantaneous,
### Table 3.3: Most common power quality problems [3, 112–130]

<table>
<thead>
<tr>
<th>Issue</th>
<th>Definition</th>
<th>Causes</th>
<th>Consequences</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Voltage dip (or sag)</td>
<td>When $V_{\text{rms}} &lt; V_{\text{nom}}$ by 10-90% for 0.5 cycle to 1 min</td>
<td>Remote system faults, customer's installation faults, heavy load switching, large motor start-ups, and poor system maintenance and protection</td>
<td>Malfunction to microprocessor-based control systems, disconnection in electric rotating machines, loss of efficiency and lifetime, and tripping of electromagnetic relays</td>
</tr>
<tr>
<td>2. Voltage swell</td>
<td>When $V_{\text{rms}} &gt; V_{\text{nom}}$ by 10-80% for 0.5 cycle to 1 min</td>
<td>Heavy load switching, poorly regulated transformers, poor system maintenance and protection, and badly designed power sources</td>
<td>Flickering of lights and screens, damage or stoppage of sensitive equipment, probable data loss, and electrical contact degradation</td>
</tr>
<tr>
<td>3. Flicker or variable fluctuation</td>
<td>Repetitive fluctuations in $V_{\text{rms}}$ between 90 and 110% of $V_{\text{nom}}$</td>
<td>Frequent switching of large loads, arc furnaces, intermittent loads, RES integration, and welding plants</td>
<td>Flickering of lights and screens, disturbing concentration, and creating headaches for people affected</td>
</tr>
<tr>
<td>4. Voltage spikes/surges</td>
<td>Abrupt alterations of voltage value for several $\mu$s - few ms</td>
<td>Switching of lines or p.f. correcting capacitors, lightning, and disconnecting heavy loads</td>
<td>Electromagnetic interference, data loss or processing errors, and damage to insulation materials and electronic components</td>
</tr>
<tr>
<td>5. Overvoltage</td>
<td>When $V_{\text{nom}}$ rises above 110% for &gt;1min</td>
<td>Load variations, inappropriate tap setting and p.f. correction, motor starting, and decrease in demand</td>
<td>Overheating, infrared process blistering, equipment damage, and reduced lifetime for lighting and electrical equipment</td>
</tr>
<tr>
<td>6. Undervoltage</td>
<td>When $V_{\text{nom}}$ drops below 90% for &gt;1min</td>
<td>Poor wiring, unbalanced phase loading, incorrect tap setting, load variations, motor starting, reclosing activity with protection devices, and increase in demand</td>
<td>Instigates thermal effect and increase system loss, hardware damage, dimming and turning-on problems of some lights, creates errors, and reduces equipment efficiency and lifetime</td>
</tr>
<tr>
<td>7. Very short interruptions</td>
<td>When electrical supply interruptions occur for few ms -1 or 2 sec duration</td>
<td>Opening and automatic reclosure of protection devices for clearing faults (due to lightning, insulator flashover, and insulation failure)</td>
<td>Malfunction to data-processing equipment and information loss, sensitive equipment stoppage, and unexpected tripping of protection devices</td>
</tr>
<tr>
<td>8. Long interruptions</td>
<td>When electrical supply interruptions occur for &gt;1 or 2 sec duration</td>
<td>Network equipment failure, acts of nature and accidents, failure or poor coordination of protection devices, fire and human errors</td>
<td>Equipment failure or shutdown, production losses, memory loss of computer or controller, and hardware damage</td>
</tr>
</tbody>
</table>

**Note:** ESS role is denoted by "Yes".
<table>
<thead>
<tr>
<th>No.</th>
<th>Transient Type</th>
<th>Description</th>
<th>Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>9.</td>
<td>Impulsive transients</td>
<td>Large increase in V or I for a very short duration (1 ns-1 ms)</td>
<td>Data loss, hardware damage for electronic equipment, and current limiting fuse operation</td>
</tr>
<tr>
<td>10.</td>
<td>Oscillatory transients</td>
<td>Occurs when V or I rapidly changes polarity (+ve to -ve)</td>
<td>Data loss, electronic interference, and microprocessor-based equipment errors</td>
</tr>
<tr>
<td>11.</td>
<td>Voltage unbalance</td>
<td>When voltage magnitudes or phase angles of a 3-φ system are not equal</td>
<td>Existence of -ve sequence and detrimental to 3-φ loads (unwanted heating, loss of efficiency etc.), maloperation of variable speed drive protection schemes and motors</td>
</tr>
<tr>
<td>12.</td>
<td>Harmonic distortion</td>
<td>V or I waveform frequencies are multiple of fundamental (i.e. non-sinusoidal waveforms)</td>
<td>Overheating of equipment and cables, loss of efficiency in equipment, electromagnetic interference, errors in data measurement, and unexpected tripping of thermal protections</td>
</tr>
<tr>
<td>13.</td>
<td>Noise</td>
<td>When high frequency signals are superimposed on fundamental frequency</td>
<td>Data processing errors, probability of data loss, and disruption to sensitive electronic equipment</td>
</tr>
<tr>
<td>14.</td>
<td>Frequency deviation</td>
<td>A deviation in fundamental frequency</td>
<td>Data loss, system crashes, unexpected faults, disconnection to a large block of loads, damage to equipment and large sources of generation forced off-line</td>
</tr>
</tbody>
</table>

\[ V_{rms} = \text{RMS voltage}, \ V_{nom} = \text{Nominal voltage}, \ \mu s = \text{Micro-seconds}, \ \text{ns} = \text{Nano-seconds}, \ V = \text{Voltage}, \ I = \text{Current}, \ p.f. = \text{Power factor}, \ \phi = \text{phase} \]
momentary, and temporary. Depending on the disturbance voltage magnitude and duration, voltage quality issues such as voltage dip (or sag), voltage swell, interruption, overvoltage, and undervoltage can be demarcated [129, 132]. The voltage profile management of large distribution networks is difficult because of the fluctuating behaviour of integrated RESs [133] and load demands [134], but it is crucial for power quality improvement. These oscillations can initiate steady state high/low voltage problems as well as voltage flickers, depending on the rate of change of voltage and various loading scenarios [135].

The exigency for ESS use to mitigate the impact of various power quality issues is highlighted in Table 2.2, which shows its potential for ameliorating most of the power quality problems in distribution networks. These include voltage dip, voltage swell, flicker, spikes or surges in voltage, overvoltage, undervoltage, short and long interruption, oscillatory transients, harmonic distortion, and deviation in frequency. For power quality improvement, ESS can be appropriate for fast, immediate, and high power responses which last for up to a few seconds [136], and for flicker compensation and voltage
3.1 Optimal placement, sizing, and operation of ESSs, and power quality issues in distribution networks

sag correction problems. For instance, they are useful for maintaining the network voltage within an endurable limit [137], which is obligatory for precise reactive power flow control and thus for generating high quality power [4]. In many cases, ESSs are introduced to solve power quality problems. As discussed in [133, 138], power quality support can be provided by implementing ESSs at the point of common coupling through converters with the exchange of active and reactive power. An ESS, as a source of power connected to a dc-link, can also be coupled to FACTS (flexible AC transmission system) or DSTATCOM (distribution static synchronous compensator) [139] devices compensate for the system’s active and/or reactive power unbalance. A new method is proposed for applying DSTATCOM with ESS to solve the flicker problem [138]. Again, ESSs are employed to offset the reactive power in [140], where the key drive is to eliminate harmonic distortions.

ESSs are used to minimize the overvoltage problem along with the function of storing excessive energy in [141–143]. Using rooftop PVs, both overvoltage and undervoltage issues are addressed in [144] and a reactive capability of a PV inverter with ESS (battery) is proposed to ensure an acceptable voltage profile. Voltage fluctuations with the penetration of PVs are addressed and mitigated by introducing customer-side ESSs in [145–147]. An advanced voltage regulation method is proposed in [148] for distribution networks. This comprises dispersed ESSs and generation systems and considers an imbalance in the load diversity among feeders. However, improved voltage stability and more precise voltage regulation are still demanding issues. The authors in [149] propose using distributed ESSs to solve the voltage rise/drop problems in distribution networks (low voltage) with high penetration of rooftop PVs. The authors propose a coordinated control method to estimate the power outputs of ESSs in this research, which includes both distributed and localized SoC controls for distributed ESSs. The impact of an ESS (VRB), integrated with a PV source, on feeder voltages is investigated in a detailed simulation; however, the scenario may be challenged by the penetration of multiple RESs (e.g., PV and wind) in distribution networks.

The voltage profile can also be improved by controlling the reactive power. In [150], a droop control strategy for an ESS (ZnBr) combined with PV inverters is proposed for reactive compensation and hence for voltage profile improvement. However, the coordination of distributed ESSs in this research is challenging as the proposed control
3. LITERATURE REVIEW, RESEARCH FOCUS, AND METHODOLOGIES

Methods are applied in a decentralized structure. The power curtailment of PV or reactive power compensation is inexorable if the SoC of the ESS at a specific bus reaches defined limits. Quite the opposite is considered in [151]: a coordinated control of ESSs (distributed) with conventional voltage regulators is proposed to mitigate the voltage rise problem where the charging/discharging coordination of distributed SoC controllers is managed by a centralized controller.

A key review paper highlights how ESSs can also be beneficial for frequency control [4]. During transients, ESSs can play a major role in maintaining frequency stability by adjusting the grid frequency dynamically and hence improving the stability of the system [4]. The regulation of grid frequency is investigated with a new SoC feedback control strategy in [152], for a system comprising high penetration of wind generation and ESS. Another frequency control approach entirely reliant on ESS (batteries) is discussed in [153] to facilitate frequency regulation of an islanded power system (with no RESs). Likewise, in [154], a peerless control algorithm with flexible SoC limits of an ESS (battery as spinning reserve application) is employed for frequency control of an isolated power system. The potential of ESSs to mitigate power quality problems and sustain healthy networks has been validated in the above literature. However, the most important goal is to extract the maximum benefit from using ESSs for power quality improvement via the optimal placement of ESSs in a distribution network. There is little research on solving power quality issues with optimal ESS placement. A number of optimization problems, such as voltage flicker, overvoltage, and undervoltage, should be addressed to realistically solve power quality problems via optimal ESS placement. For example, if the ESS location is selected arbitrarily in a network where the voltage flicker or dip problem does not generally exist, then the ESS placement will not mitigate network power quality problems, which may happen for other power quality issues set out in Table 3.3.

3.2 IMPLEMENTATION AND PERFORMANCE

The relevant literature for optimal ESS placement, sizing and operation, and related power quality issues has been reviewed in the preceding section. Below, development and implementation challenges, optimization approaches to obtain ideal distribution network
3.2 Implementation and performance

performance, the social impact of ESS placement, and related energy security issues are discussed.

3.2.1 Development and implementation challenges

For optimal ESS placement, development and implementation challenges must be considered. Development issues include appropriate planning and modeling, realistic data analysis, determination of optimization factors (such as power quality problems, cost, stability, and reliability issues), suitable ESS selection and sizing should be addressed thoroughly, while initial investment, ESS deployment barriers, and performance analysis after placement are important implementation issues.

Appropriate planning and system modeling are essential first development steps for optimal ESS placement in a distribution network. Following this, a thorough analysis of realistic data for that network should be undertaken to identify various network problems. Subsequently, the important factors for optimization should be determined for a location or multiple locations in that network. Finally, the appropriate selection of ESSs and their sizes can be completed in order to target the problems, optimization factors, and network benefits.

A key implementation challenge is the substantial initial investment for ESSs. Additional deployment barriers include:

(a) Utility processes and regulations not favouring the ESSs;

(b) Insufficient awareness of ESS benefits among stakeholders [155].

Another important issue is the lack of large-scale production to meet required power and energy capabilities, especially for distribution network levels [155]. These problems can be solved through enlisting government funding support, streamlined supervisory approvals, and offers of tax incentives to encourage investors to focus on specific ESS technology [155]. After deploying ESSs in a distribution network, performance analysis is also important.
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3.2.2 Optimization approaches in achieving optimum performance

3.2.2.1 Various optimization approaches

Choosing the optimal places and sizes of ESSs in a distribution network is not straightforward. To maximize distribution network performance, the appropriate selection of optimization approaches is another key benchmark. There are various categories of optimization methods, such as classical, analytical, and meta-heuristic [156–158]. Although these types of optimization approaches are suitable for some applications, they also have disadvantages. The OPF, a classical approach, is suitable for highly complex problems, but has limitations for power systems with high dimensionality [159]. Similarly, although linear programming is easy to implement [109], it is generally difficult to represent models as a set of linear equations [160]. Analytical approaches are suitable for small and simplistic systems with few state variables and provide very accurate results relatively quickly. Nevertheless, their selection is not appropriate for large and complex system, especially in less straightforward applications, with size complications and the varied characteristics of distribution networks. They may also generate imprecise solutions for real time problems [157]. Some examples of this category are the PEM, eigen-value-based analysis (EVA), index method (IM) and sensitivity-based method (SBM). Meta-heuristic approaches are most appropriate for solving challenging problems in distribution networks (many of these are inspired by nature) and are capable of providing accurate, efficient, and optimal solutions. However, meta-heuristic techniques also have some limitations since they do not always offer the optimal solution, and in most real-life problems, some assumptions cannot be satisfied. Algorithms in this category include GA, PSO, artificial bee colony (ABC), ant colony optimization (ACO), harmony search, chaotic algorithms.

Meta-heuristic techniques are considered in several studies for optimizing the placement, sizing, and operation of ESSs in power networks. A GA is used in [161] to place and size a single ESS in order to achieve network benefits in relation to the reduction of voltage deviation, losses, and costs. GAs are also applied in [162] to determine control strategies, e.g., controlled gain factors for hybrid power generation and in [163] for ESS sizing and operation to help defer investment, manage electricity price arbitrage,
and reduce access costs for transmission. Furthermore, GA is employed in [81] for optimal ESS allocation and operation when facilitating large-scale wind power integration. Again, GA is used to place an ESS (SMES) in [164] to maximize the voltage stability index. Another meta-heuristic approach, PSO, is used in [85] for optimum allocation of standby ESSs to minimize distribution network costs. In [57], the PSO is applied to ESS sizing and the minimization of the total levelized cost, while achieving cost benefits for an ESS used in a grid-connected, stand-alone PV system for both short- and mid-term periods. In [83], a fuzzy PSO, associated with a cost benefit analysis, is employed for optimal allocation of ESSs to mitigate risk for distribution companies (DISCOs). In [56], the advanced artificial neural network (ANN) is utilized for optimal ESS sizing in a large-scale wind farm while increasing output predictability and reducing wind integration cost. The results are compared with other approaches, e.g., general, fuzzy, and simple ANN. A tabu search (TS) algorithm is used in [165] for ESS sizing by taking into account unit commitment. The multi-objective strength pareto evolutionary algorithm 2 (SPEA2) [166] is utilized in [167] to place multiple ESSs in a distribution network intended to providing arbitrage and ancillary services as well as voltage support. Simulated annealing (SA) is applied to ESS allocation in [168] to offer an emergency backup service for power networks: it allows non-improving moves to be detected for escaping local optima [169].

Although meta-heuristics having some advantages, they do not have strong global and local search abilities and hence do not always guarantee a globally optimal solution compared to classical approaches such as linear programming. For instance, the ABC algorithm, which is recognized as a relatively new bio-inspired swarm intelligence approach, is competitive with other population-based algorithms [170, 171] but can be trapped in local optima when global optimization is sought, as reported in [172]. Research continues with the intention of improving the existing approaches and hybridizing meta-heuristic approaches with other approaches or their modifications to offer more effective solutions [157, 173].

### 3.2.2.2 Hybrid meta-heuristic approaches

The hybridization of a meta-heuristic with other optimization algorithms, known as the hybrid meta-heuristic approach, may achieve globally optimal solutions and provide
optimum solutions to distribution network problems according to [157] which presents a detailed picture of all methods in different categories and concludes in favour of hybrid meta-heuristic approaches. The hybrid meta-heuristic techniques combine two or more algorithms having different strengths and offer the best solution by eliminating limitations of a single meta-heuristic approach. These techniques can be robust and powerful tools for global optimization, can tackle various multi-objective (constrained and unconstrained) problems, and obtain high-quality results with relatively few function evaluations [157]. For instance, the ABC has poor local search ability but strong global search capability [174], while the reverse is true for PSO [175]. The ABC algorithm is combined with PSO in [176] to eliminate shortcomings and provide a well-balanced hybrid with powerful local and global searching abilities. To evade the major shortcomings of the classical simple GA, a new hybrid algorithm combining GA and TS is proposed in [177]. In another example, ACO and ABC are amalgamated to blend their continuous and discrete optimization features and develop a new hybrid ACO-ABC-based optimization algorithm [178]. Similarly, the ABC algorithm is merged with the harmony search in [179] and the chaotic algorithm in [180] to overcome its major limitation and achieve a best global optimization approach along with a strong local search ability.

The PSO is hybridized by integrating non-dominated sorting genetic algorithm II (NSGA-II) in [80] for ESS placement and sizing in a distribution network that addresses wind power uncertainty. To obtain an optimal solution for the ESS placement, sizing, and operation problems and minimize the complexity of objective functions, the GA is combined with linear programming in [23, 82], and with a sequential quadratic programming technique to place capacitors and ESS in [54]. The GA is combined with a market-based probabilistic OPF in [84] for the optimal placement of ESSs in a deregulated power system with high wind penetration.

Thus, hybrid meta-heuristic approaches can be applied as robust methods for the optimization of complex, nonlinear objective functions which not only enhance the potential for exploitation and convergence but also provide better results [157]. As these techniques offer optimum solutions with a reduced number of iterations, they can be used to deal with distribution network problems with regard to ESS placement, sizing, and operation and can facilitate the optimum performance of distribution networks.
3.2 Implementation and performance

3.2.3 Social impact and energy security

It is crucial to be aware of the distribution grid situation, deal with real-time grid problems and yield optimum solutions. Since the optimal placement, sizing, and operation of ESSs can mitigate the related grid problems of power quality and the sudden increase or decrease in load demand, these strategies can contribute to the optimum performance of the distribution network and ensure a quality power supply to consumers. Moreover, the optimal placement of ESSs assists in avoiding distribution network expansion costs as demand rises. Furthermore, the optimal control or operation of ESSs allows the operators of electrical distribution systems to improve reactive control and reduce overall costs.

Due to the lack of new generation capacity and the risk of fuel costs increasing, deregulated electricity markets are developing in most advanced countries to promote competition in electricity supply markets. The restructuring of these markets has led to distinct generation, transmission, distribution, and retailing processes. One of the outcomes of market-place reform is the emergence of third-party entities known as retailers who procure electricity from various electricity sources (e.g., the electricity pool, spot markets, and self-production units), and resell it as the sole provider to customers [181, 182]. Retailers need to make effective decisions about sources and the amount of electricity they procure, as these electricity sources have different variable characteristics over time [183, 184]. Retailers generally try to manage the risk involved in purchasing electricity from those sources by offering fixed or variable electricity prices to their consumers. However, load uncertainty still creates risks, which can be accommodated by the flexible operation of ESSs and implementing smart scheduling strategies while optimizing the cost of energy purchased [23, 82, 95]. In this context, optimally placed ESSs may be an effective way for retailers to manage variable loads and reduce risks while optimizing their profits and consumer satisfaction.

More importantly, the optimal placement of ESSs will encourage operators to add more RES generation (e.g., solar and wind) to the grid supply. For instance, the world’s largest ESS (Li-ion) of 100MW capacity is installed by Tesla in South Australia. The ESS is integrated with a wind farm and capable of powering 30,000 homes for up to an hour in the event of a blackout [185]. Thus, the placement of such ESSs makes the
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grid supply more environmentally sustainable and reliable without hampering other non-renewable generation and profit making opportunities for the operators. As achieving energy security is a high priority for a society, optimal ESS placement, sizing, and operation can provide safe and secure energy management.

3.3 Conclusions

This chapter has provided a comprehensive overview of the issues relating to the use of ESSs in electricity networks. It has presented some key ideas for ESS placement, sizing and operation, and the mitigation possibilities of power quality issues by ESS placement. Furthermore, for optimal ESS placement, this study has identified development and implementation challenges, and has discussed the suitability of hybrid meta-heuristic optimization approaches, and has also considered social impact. Some recommendations are provided at the end of this section. However, more research is needed on the impacts of ESS placement in a distribution network in relation to optimum demand management, power quality management, the cost of the distribution network, power loss reduction, RES or DG integration, and grid stability and reliability. Through understanding ESS placement issues and possible impacts after placement, the deployment of ESSs in a distribution network and the associated development of smart grids will be greatly facilitated.

Overall, ESSs can improve the performance of a distribution network. The objectives for attaining desirable enhancements such as energy savings, distribution cost reduction, optimal demand management, and power quality management or improvement in a distribution network through the implementation of ESSs can be facilitated by optimal ESS placement, sizing, and operation in a distribution network. Optimal ESS placement, along with sizing and operation, are highly important for greater RES integration in the distribution network and thus for reduced carbon emissions. After reviewing the available research work on ESS placement, sizing and operation issues, the following recommendations are made for future research to address the identified gaps:

- Optimal ESS sizing should be accomplished by considering all costs directly related to the benefits of selected case studies and after determining the optimal
ESS locations in a particular network. Furthermore, a comparison of the selected ESS (after sizing) with other possible types in regard to cost and performance is recommended to explore an appropriate ESS option for a specific location in a distribution network.

- If RESs are integrated in the distribution grid, the uncertainties associated with renewables should be addressed when optimizing ESS placement. Moreover, due to the intermittency of many RESs, the consideration of power quality issues in problem formulation is highly recommended.

- For demand-side management and appropriate system modeling with fluctuating loads and EVs, load and EV uncertainties must be considered in the optimal ESS placement problem. The EV charging impacts to distribution networks should also be incorporated during system modeling and objective function formulation. Moreover, various ESS control approaches (e.g., MAS) can be employed to facilitate optimal ESS operation in distribution networks.

- The optimal solution of ESS placement problems directly relies on case studies, especially in regard to network topology and system size. The number of required ESSs in an LV distribution network may be lower than in an MV network, and the distributed structure of ESS placement with more than one ESS is highly recommended to allow better system performance and flexibility in mitigating problems.

- As global warming and pollution are pressing issues, environmental and geographical constraints must be considered along with technical and economic constraints to provide a realistic solution for optimal ESS placement. For instance, the installation of ESSs should not be allowed in certain buses of distribution networks due to right of way issues. Some environmental and geographical constraints are neglected during problem formulation in a large portion of the literature (see the research summarised in Table 3.2).

- Although many strategies have been applied for tackling optimal ESS placement, sizing, and operation problems, more research effort should be applied to optimizing transient/dynamic issues rather than the steady state characteristics of a distribution network. The reliability of a distribution network with ESSs should
be analyzed through the verification of reliability indices such as SAIDI, SAIFI, CAIDI, CTAIDI, CAIFI, MAIFI, ASIFI, ASAI, ASIDI, CEMIn, and CELID.

- Some major power quality problems can be mitigated by optimal ESS placement and operation as indicated in Table 3.3. Therefore, issues such as voltage flicker and overvoltage or undervoltage should be specified for a particular network place and included in the optimization problem.

- Although several meta-heuristic approaches for optimization have already been established by researchers, improvement is still required. The hybridization of a meta-heuristic with other optimization algorithms (namely hybrid meta-heuristic), with proper setting of control parameters, or developing more efficient meta-heuristic approaches for global optimum search is recommended.

3.4 Research questions

On the basis of the findings and challenges as identified through above literature survey in relation to ESS placement and sizing, and power quality, the present research is carried out by addressing following research questions (RQs):

(i) **RQ1**: In case of optimal placement and sizing of distributed ESSs using P injection approach only, how the performance parameters (voltage deviation, power losses, and line loading) of distribution networks can be minimized that are affected by RES and load characteristics, various constraints, and optimization parameters? Moreover, what are the values of performance indices that indicate performance improvement? How the optimization results can be validated through the application of two optimization algorithms?

(ii) **RQ2**: How much improvements in percentage can be achieved while using PQ injection-based ESS placement and sizing approach compared to P injection-based approach? How the optimization results can be verified through the application of two optimization algorithms?

(iii) **RQ3**: How much performance and power quality of distribution networks can be improved simultaneously through the placement and sizing of distributed ESSs (as
evaluated by performance indices)? How the optimization strategy can optimize the expected objective function parameters that are affected by RES and load characteristics, various constraints, and optimization parameters? How the optimization results can be validated through the application of two optimization algorithms?

(iv) RQ4: How to place and size a grid-scale BESS to improve frequency response of transmission networks? How the optimization strategy can simultaneously minimize frequency deviation and ROCOF, and tune the BESS controller parameters while the network is affected by amount of RES integration, various network events and constraints, and optimization parameters? What is the total expected ESS size in terms of power and energy? How the optimization results can be justified through the application of two optimization algorithms?

3.5 Research methodologies

The methodologies of this research project is depicted in Fig. 3.2 (in an abridged form), which represents the overall work flow for addressing the above research questions. DIgSILENT PowerFactory provides useful solutions for distribution network problems such as system design, modeling and optimization capabilities, grid interaction skills in a multi-user environment, and data handling [186]. Hence, the DIgSILENT PowerFactory is used as the main tool for system modeling and analysis. Python programming language is used to control the system models developed in PowerFactory and to facilitate the optimization processes. The configuration of the used computer for conducting the optimization is: Intel(R) Xeon 3.5 GHz processor, 16 GB RAM, 64-bit windows 10.

In this study, the load characteristics associated with electrical demand are collected from published literature which is presented in Chapter 4 [187, 188]. The IEEE-33 bus network is used for modeling of distribution networks where the data can be found in [187, 189] (as presented in Chapter 4 Appendix). The RES generation profiles (for both wind and solar) used for distribution networks are taken from [187]. The IEEE-39 bus is utilized as a test model of transmission networks which is an equivalent transmission system model of the New England area and Canada (in the northeast of the U.S.A.). The data of this IEEE-39 bus system is taken from [190, 191] and provided in Appendix C.
Various parameter data of the dynamic BESS model is presented in Chapter 7 Appendix [192].

The optimization algorithms for ABC, FSCABC, and PSO are implemented using Python language. The step-wise implementation of each research objective is presented in various chapters (Chapter 4 to Chapter 7) of this thesis. The Python scripts written for fulfilling various research objectives and all system models developed in PowerFactory are included in Appendix D. The decision variables of an optimization process are recorded and the detailed system results are generated from the PowerFactory. The performance analysis is performed for every research objectives to obtain the required outcome as given in Fig. 3.2 and performance indices are evaluated to monitor the performance improvements.
Chapter 3 references


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Chapter 4

Optimal ESS Placement and Sizing in Distribution Networks Using P Injection Approach

This chapter addresses Research Question 1 (RQ1) and proposes a strategy for optimal placement of distributed ESSs in distribution networks to minimize voltage deviation, line loading, and power losses.¹ The optimal placement of distributed ESSs is investigated in a medium voltage IEEE-33 bus distribution system, which is influenced by a high penetration of renewable (solar and wind) distributed generation, for two scenarios: (1) with a uniform ESS size and (2) with non-uniform ESS sizes. System models for the proposed implementations are developed, analyzed, and tested using DIgSILENT PowerFactory. The artificial bee colony optimization approach is employed to optimize the objective function parameters through a Python script automating simulation events in PowerFactory. The optimization results, obtained from the artificial bee colony (ABC) approach, are also compared with the use of a particle swarm optimization (PSO) algorithm. The simulation results suggest that the proposed ESS placement approach can

4.1 Introduction

Present power systems face a period of rapid change driven by various interrelated issues, e.g., demand management [1], greenhouse gas (GHG) reduction targets [2], integration of renewables [3, 4], power congestion [5], power quality requirements [6, 7], and network expansion [8] and reliability [6, 7]. For distribution networks, an energy storage system (ESS) converts electrical energy from a power network, via an external interface, into a form that can be stored and converted back to electrical energy when needed [9]. Depending on the demand or cost benefits, the ESS can store energy to produce and discharge electricity [10]. Consequently, ESSs are increasingly being embedded in distribution networks to offer technical, economic, and environmental advantages. These include mitigation of voltage deviation [11, 12], facilitation of renewable energy source (RES) integration [13–15], distributed generation planning [16] and RES energy time-shifting [17], load shifting [18–21], load levelling [22] and peak shaving [23], power quality improvement [5, 11, 24, 25], frequency regulation [5, 26], network expansion [27, 28] and overall cost reduction [29, 30], operating reserves [5, 31], GHG reduction [32–34], profit maximization [5, 35], and network reliability [36].

Unfortunately, misplacement or misuse of ESSs in distribution networks can adversely affect network performance [37], voltage and frequency regulation, power quality, reliability, and load controllability. Appropriate ESS placement can facilitate an optimal ESS operation for voltage and power quality improvement [5, 12, 24, 25], peak demand mitigation [12], relief of distribution congestion [5, 25], power flow adjustment [5], power loss reduction [12, 25], network reliability [36], overall network cost reduction [36, 38], RESs integration [27, 39, 40], and system effectiveness [36, 41]. As the use of large-scale ESSs in distribution networks involves substantial investment, placing ESSs optimally on the basis of performance expectations is challenging and has been addressed in several studies [5, 11, 12, 24, 25, 27, 29, 30, 36, 38, 39, 41–51].
Asset management of distribution networks is an essential task of network service providers to ensure safe and secure operation of the networks. However, this can be an expensive task that also might result in a high network cost and thereby can significantly affect electricity prices. This cost could include network reinforcement for thermal and voltage stability. Therefore, the motivation of this work is to provide low cost solutions to distribution network operators for a better asset management practice.

A comprehensive review, regarding ESS placement to mitigate the issues of distribution networks, is presented in [9]. An optimal allocation and sizing of ESSs, for an IEEE-30 wind power distribution system, is accomplished in [24], while focusing on power system cost minimization and voltage profile improvement. The authors employ a hybrid multi-objective PSO incorporating a non-dominated sorting genetic algorithm (NSGA-II), a probabilistic load flow technique, and a five-point estimation method (5PEM).

In [42], a multi-objective ESS allocation is performed for both transmission and distribution networks. A detailed analysis, termed as sensitive analysis, is accomplished on the transmission side using complex-valued neural networks, time domain power flow, and economic dispatch to locate the ESSs. On distribution side, the optimal ESS size is estimated to address load curve smoothing and peak load shaving. Ref. [41] proposes optimal distributed ESS planning (specifying locations and sizes) in soft open points-based distribution networks embedding the reactive power capability of distributed generators (DGs) and the network reconfiguration through a mixed-integer second order cone programming (MISOCP) approach. Ref. [29] formulates an optimal ESS placement problem embedding network reconfiguration in an RES-integrated distribution network to minimize overall system costs, while employing a mixed-integer linear programming (MILP) approach.

Optimal ESS location and size are determined in [43] for load management, minimization of net present value (NPV), and total cost while maximizing distribution system benefits. A genetic algorithm (GA) combined with a linear programming solver, a sequential Monte Carlo simulation (MCS), and MATLAB optimization toolbox are used for different aspects of the investigations. The same approaches are used in [36] and [30] to establish optimal ESS allocations in different situations. Ref. [36] accomplishes optimal ESS allocation, targeting minimization of interruption cost and annual cost, and
improvement of distribution system reliability. On the other hand, distribution network benefits are maximized in [30] by reducing the cost of ESS installation, maintenance, interruptions, system upgrades, and energy losses.

An optimal allocation of distributed community ESSs in distribution networks is proposed in [27] to gain the benefits from peaking PV generation, energy arbitrage, energy loss reduction, emission reduction, network upgrade deferral, and Var support. Ref. [38] proposes a network-aware strategy for the planning and control of ESSs in an RES-penetrated distribution network to minimize investment and operational costs. [44] analyzes the impact of ESS location and configuration on power losses, voltage profiles, and ESS utilization within a feeder of low voltage (LV) distribution networks.

The mitigation of voltage deviations and improvement of supply quality, elimination of load curtailment and line congestions, and minimization of distribution network costs and electricity costs are achieved through the optimal placement and sizing of ESSs, while using AC-optimal power flow (AC-OPF) and MISOCP approaches in [11]. In [45], a fuzzy PSO (FPSO) approach is employed to mitigate the risk to distribution companies by optimizing ESS allocation, while maximizing energy transaction profits and reducing operational costs.

In [5], a MILP model is proposed to maximize the net profit of distributed ESSs while achieving distribution system congestion management, energy price arbitrage and energy reserve, and a frequency regulation service via active and reactive power controls. In [39], the ESS allocation is able to minimize the voltage fluctuation problems (due to PV integrations in LV networks) by applying a GA-based strategy hybridized with simulated annealing, while [46] employs a GA-based bi-level optimization approach to mitigate the same problem. Again in [25], an alternating direction approach to multipliers is employed for allocation of distributed ESSs to provide voltage support and to minimize both network losses and the cost of energy in relation to external grid and congestion management.

In [47], optimal ESS placement and sizing is accomplished and validated through mathematical modeling and the OPF approach. A game-theoretic multi-agent approach is proposed in [48] for optimal ESS allocation to mitigate the risk of energy transaction
4. OPTIMAL ESS PLACEMENT AND SIZING IN DISTRIBUTION NETWORKS USING P INJECTION APPROACH

mechanisms for energy agents. In [49], optimal ESS allocation in LV distribution networks is accomplished through multi-period OPF and clustering and sensitivity analysis approaches to prevent under- and over-voltages and to minimize total network costs (in regard to ESS and network losses).

A framework for optimal ESS placement in a wind-penetrated deregulated power system is developed in [50] to maximize the utilization of wind power and minimize the hourly social cost. Market-based probabilistic OPF, GA, and an energy arbitrage model are applied to optimize, evaluate, and analyze the system model. An auto-regression moving average modeling technique, for optimal ESS placement in a wind-penetrated distribution grid, is proposed to minimize the annual electricity cost without considering peak shaving and reliability enhancement in [51]. [12] achieves optimally distributed ESS allocation and operation in order to improve load and generation hosting ability, while using a cost-based multi-objective optimization strategy through MATLAB. As a result, power loss and peak demand are reduced, with better voltage regulation.

Although various distribution network issues are addressed in the above literature, very few studies [12] focus on line loading minimization, power loss reduction, and voltage profile improvement. However, the operational costs of distribution networks are largely dependent on these parameters which can be minimized through optimal distributed ESS placement. For a large distribution network, distributed ESS placement provides more opportunities for problem mitigation and greater flexibility than centralized placement [24, 50]. For instance, this approach helps to fix the voltage deviation in buses promptly, which is done generally with on-load tap changers, capacitors and voltage regulators [52]. In some research [30, 36, 43, 48] (as discussed above) the ESS types, such as lead-acid, vanadium redox (VR), sodium sulfur (NaS), compressed air energy storage (CAES), and Li-ion, are specified. Other research [11, 24, 25, 27, 39, 41] does not specify ESS types. However, in [12, 42, 44, 46] ESS name is mentioned as battery ESS (BESS) rather than specifying the ESS technology, e.g., lead-acid, Li-ion or other.

The determination of optimal ESS locations in a distribution network involves one or more optimization problems depending on the benefits targeted. Various optimization and modeling techniques are employed for the optimal placement of ESSs in the above literature [5, 11, 12, 24, 25, 27, 29, 30, 36, 38, 39, 41–45, 47–51]. The research described
in this chapter introduces ABC meta-heuristic optimization for optimal ESS placement. Being simple and robust, the ABC algorithm is capable of solving even complex combinatorial and multi-dimensional optimization problems [53, 54]. The likelihood of finding an optimum solution is enhanced by the algorithm’s triple search capability, which is based on the search stages of three groups of bees [55, 56]. The robustness and efficiency of the ABC algorithm in solving global optimization problems (both constrained and unconstrained) is demonstrated in various comparative studies that compare the ABC algorithm to other well-known modern heuristic algorithms such as GA, DE, and PSO [55, 56].

In this research, a comprehensive investigation is carried out for optimal ESS placement in an IEEE-33 bus distribution network, in a distributed manner. DIgSILENT PowerFactory provides useful solutions for distribution network problems such as system design, modeling and optimization capabilities, grid interaction skills in a multi-user environment, and data handling [57]. As a result, it is used as the main tool for system modeling and analysis. Python programming language is used to control the system models developed in PowerFactory and to facilitate the ABC optimization. Furthermore, a new form of lead-acid battery, the Ultrabattery, is selected as the ESS technology and is used in this research.

The main contributions of this chapter are summarized as follows:

- The optimal placement of ESSs is investigated focusing on line loading reduction, real and reactive power loss minimization, voltage profile improvement, and ultimately cost minimization. All of the parameters, incorporated in the objective function, are related to costs of distribution network reinforcement for thermal and voltage stability, and lower asset management. These parameters have not been widely considered together for optimal ESS placement by other studies such as [24, 25, 44, 49]. Furthermore, some important constraints which are rarely used by earlier works such as voltage unbalance factor (VUF) and line loading constraints are imposed in this study.
The overall investigation for optimal ESS placement is conducted in two different categories: (1) with a uniform ESS size, and (2) with non-uniform ESS sizes. These type of investigations have not been conducted by earlier works such as [11, 12, 25, 44, 45, 48, 50, 51]. The results from these investigations are analyzed and compared. Although the ABC approach is used for these investigations, PSO algorithm is also applied to justify the optimality of results obtained from ABC optimization technique.

The performance indices are evaluated and a cost comparison for various case studies is presented. These performance indices assist to follow-up the performance improvement after ESS allocation in a distribution network, which are not evaluated by related studies in the literature.

4.2 System modeling

4.2.1 ESS selection and modeling

The appropriate selection of grid-scale ESSs depends on various factors such as required system performance, system capacity, type of application, and ESS cost and reliability [9, 58, 59]. Various ESS options for distribution networks, to be explored in terms of technical characteristics and application benefits, are discussed in [9, 60, 61]. A recent ESS, namely Ultrabattery (also known as an advanced lead-acid battery), is frequently being incorporated in grid-scale applications in the U.S. and Australia, due to its improved performance and lower cost in comparison with other electrochemical ESSs (e.g., lead-acid) [62, 63]. The lead sulfate accumulation problem of lead-acid batteries is reduced in the Ultrabattery by incorporating carbons and forming a supercapacitor. Given the above considerations, Ultrabatteries are chosen as ESSs in this research.

Although the Ultrabattery is chosen as the ESS technology in this research, the ESS model is considered as generic and can be applied to other ESS technologies. The ESS model should be subjected to the following conditions:

- If state of charge \( SOC^k_{ESS} = 1 \), the ESS is fully charged and if \( SOC^k_{ESS} = 0 \), the ESS is fully discharged.
4.2 System modeling

- The ESS should be able to control the active power in both ways and the $SOC_{ESS}^k$ is subject to following constraint [64]:

$$0.2 \leq SOC_{ESS}^k \leq 0.9$$ (4.1)

- A priority for the active and reactive power (P and Q) is needed to satisfy the apparent rated power, $S_{app} = \sqrt{P^2 + Q^2}$.

Additionally, the proposed ESS should fulfill boundary conditions from (4.2) to (4.7) in time $t$ (indexed 1, ..., $NT$) [12, 65]. The charging and discharging rates are determined by (4.2) and (4.3), respectively, by applying the generator convention (the charging power is positive i.e. $P_{ESS,c}^t > 0$ and the discharging power is negative i.e. $P_{ESS,d}^t < 0$) [66]. The energy storing process and charging power of the ESS are restricted by (4.4) and (4.5) respectively. Moreover, the limitations of released energy from the ESS and power discharged by the ESS are demonstrated by (4.6) and (4.7) respectively.

Charging mode:

$$P_{ESS,c}^t = \max \left\{ P_{ESS-min}, \frac{(E_{ESS}^t - S_{ESS-max})}{\eta_c \cdot \Delta t} \right\}$$ (4.2)

$$P_{ESS,d}^t = \min \left\{ P_{ESS-max}, \frac{(E_{ESS}^t - S_{ESS-min}) \eta_d}{\Delta t} \right\}$$ (4.3)

Discharging mode:

$$E_{ESS}^{t+1} = \min \left\{ (E_{ESS}^t - \Delta t \cdot P_{ESS,c}^t \eta_c), S_{ESS-max} \right\}$$ (4.4)

$$P_{ESS,c}^t \leq P_{ESS}^t \leq P_{ESS,d}^t$$ (4.5)

$$E_{ESS}^{t+1} = \max \left\{ (E_{ESS}^t - \Delta t \cdot \frac{P_{ESS,d}^t}{\eta_d}), S_{ESS-min} \right\}$$ (4.6)

$$P_{ESS,c}^t \leq P_{ESS}^t \leq P_{ESS,d}^t$$ (4.7)

4.2.2 Distribution network model

The modeling of the proposed medium voltage (MV) distribution network is accomplished in DlgsILENT PowerFactory. The single line diagram of the proposed system
Figure 4.1: Single-line diagram of the proposed distribution network model (ESS placement for Case 2(I)).

(for the case of optimal ESS placement with a uniform ESS size) is depicted in Fig. 4.1, where the IEEE-33 bus radial distribution system is used to model the overall system. The IEEE-33 bus system has been selected in this research as it is a suitable network for analyzing the proposed approach at an MV distribution level. The buses and lines are denoted by the letters B and L, respectively. The loads, solar DGs, and wind DGs are modeled using built-in templates of PowerFactory and configured according to system data found in [12, 67]. The ESS model, described in Section 4.2.1, is placed on the network in a distributed manner. The chosen base MVA and substation voltage are 10
4.3 Problem formulation

4.3.1 Objective function

The objective function (4.8) is formulated to solve the optimal distributed ESS placement problem using (4.9) to (4.15) [12, 69]. The cost function includes the costs regarding network reinforcement for thermal and voltage stability, and lower asset management of distribution networks. Overall cost minimization is achieved by minimizing the sum of cost factors, e.g., performance costs \( C^{\text{performance}}_{nVD}, C^{\text{performance}}_{PL}, \) and \( C^{\text{performance}}_{LL} \) and ESS cost \( C^{UT}_{ESS} \), while satisfying the necessary constraints. The cost factors are weighted equally with \( \gamma_{VD} = \gamma_{PL} = \gamma_{LL} = \gamma_{ESS} = 1 \).

\[
\delta(C_{Fi}) = \min_{C_{\text{performance}}} \left\{ \left( \gamma_{VD} \cdot C^{n}_{VD} + \gamma_{PL} \cdot C^{l}_{PL} + \gamma_{LL} \cdot C^{l}_{LL} \right) + \left( \gamma_{ESS} \cdot C^{UT}_{ESS} \right) \right\} \tag{4.8}
\]

where,

\[
C^{n}_{VD} = \left( \sum_{n=1}^{N} |V_{\text{target}} - V_{bi}(s^{n}_{ESS}, \lambda^{n}_{ESS})| \right) \cdot \Gamma_{VD} \tag{4.9}
\]

\[
C^{l}_{PL} = \left( \sqrt{\left\{ P_{LT}(s^{l}_{ESS}, \lambda^{l}_{ESS}) \right\}^2 + \left\{ Q_{LT}(s^{l}_{ESS}, \lambda^{l}_{ESS}) \right\}^2} \right) \cdot \Gamma_{loss} \tag{4.10}
\]

\[
P_{LT}(s^{l}_{ESS}, \lambda^{l}_{ESS}) = \sum_{i=1}^{M} P_{L}(i, j) = \sum_{i=1}^{M} \left( R_{L}(i, j) \cdot \frac{P_{L}^2(i) + Q_{L}^2(i)}{|V_{bi}(s^{l}_{ESS}, \lambda^{l}_{ESS})|^2} \right) \tag{4.11}
\]
4. OPTIMAL ESS PLACEMENT AND SIZING IN DISTRIBUTION NETWORKS USING P INJECTION APPROACH

\[ Q_{LT}(S_{ESS}^i, \lambda_{ESS}^i) = \sum_{l=1}^{M} Q_L(i, j) = \sum_{l=1}^{M} \left( X_L(i, j) \cdot \frac{P_i^2 + Q_i^2}{\left| V_{bi}(S_{ESS}^i, \lambda_{ESS}^i) \right|} \right) \] (4.12)

\[ C_{LL}^i = \sum_{l=1}^{M} \left( \% LL_{ESS}(S_{ESS}^i, \lambda_{ESS}^i) \right) \cdot \Gamma_{LL} \] (4.13)

\[ \% LL_{ESS}(S_{ESS}^i, \lambda_{ESS}^i) = \left( \frac{S_{L_{ESS}}^i}{S_{L_{rated}}^i} \right) \times 100 \] (4.14)

The total ESS unit cost is calculated as follows [70]:

\[ C_{UT}^{ESS} = \sum_{i=1}^{K} S_{ESS}^i \cdot UUC \] (4.15)

In the above equations, \( \Gamma_{VD} = 0.142 \) \$/p.u. [12], \( \Gamma_{loss} = 0.265 \$/kWh [71], \( \Gamma_{LL} = 0.503 \) \$/p.u. [71], and \( V_{target} = 1 \) p.u.. In addition, the \( UUC \) for commercial and industrial energy management applications is considered as 460 \$/kWh [72].

4.3.2 Objective function constraints

The objective function of (4.8) is subject to (4.16) to (4.26) together with ESS modeling equations as given in (4.1) to (4.7):

\[ P_i^0 + \sum_{j \in J_+} (P_{j \rightarrow i}^d) = P_i^c + \sum_{k \in J_-} (P_{i \rightarrow k}^d) \] (4.16)

\[ Q_i^0 + \sum_{j \in J_+} (Q_{j \rightarrow i}^d) = Q_i^c + \sum_{k \in J_-} (Q_{i \rightarrow k}^d) \] (4.17)

\[ V_{\min} < |V_{bi}| < V_{\max} \] (4.18)

\[ VUF < VUF_{\max} \] (4.19)

\[ VUF = \sum_{i=1}^{n} \frac{V_i^+}{V_i^-} \times 100 \] (4.20)

\[ SL_{l-t}^l < SL_{l}^{\max} \] (4.21)

\[ \lambda_{ESS}^i = \begin{cases} 0, & \text{if the ESS is active} \\ 1, & \text{otherwise} \end{cases} \] (4.22)
4.4 Optimization and proposed approach

\[ S^i_{ESS} = \begin{cases} \text{Assign,} & \text{if } \lambda^i_{ESS} = 0 \\ 0, & \text{if } \lambda^i_{ESS} = 1 \end{cases} \quad (4.23) \]

\[ P_{ESS-min} < P_{ESS} < P_{ESS-max} \quad (4.24) \]

\[ P^t_{ESS,c} \leq P^t_{ESS} \leq P^t_{ESS,d} \quad (4.25) \]

\[ E_{ESS-min} < E_{ESS} < E_{ESS-max} \quad (4.26) \]

where,

- (4.16) and (4.17) denote that the real and reactive power delivered to and from a bus \( i \) must be balanced [73].

- (4.18) indicates the voltage magnitude constraint of each node. (4.19) denotes a constraint for voltage unbalanced factor (VUF) as defined in (4.20) to avoid any voltage imbalance due to voltage fluctuations. The \( VUF = 0 \) indicates perfectly balanced voltages in a distribution system and generally \( VUF_{max} = 1 \) [12].

- (4.21) ensures that the line loading of a line \( l \) should not exceed the maximum limit \( SL^l_{max} \) to ensure the cable’s thermal stability. By referring to industry practices of planning, the operation of distribution networks should not exceed 80% loading on the substation exit cables [74]. Hence, an 80% maximum loading target of a line \( l \) is imposed in the algorithm. This also ensures that there is sufficient spare capacity among feeders to back each other during outages.

- (4.22) and (4.23) represent the ESS allocation constraints.

- (4.24) to (4.26) ensures that the power or energy of ESSs should not exceed their boundary limits during charging and discharging [12]. In addition, (4.1) to (4.7) ensure the ESS operation within the SOC limit.

4.4 Optimization and proposed approach

4.4.1 ABC optimization approach

In this study, the ABC algorithm is employed for optimizing the grid-connected ESS allocation problem. The ABC algorithm is a relatively new bio-inspired swarm
intelligence approach and one of the recent metaheuristic search techniques proposed by Karaboga in 2005 [75]. This algorithm is proposed to simulate the intelligent foraging behaviour of honey bees. This has the advantage of using fewer control parameters [54, 76]. The colony consists of three types of bees in the ABC algorithm: employed bees, onlooker bees, and scout bees. Specifically, its robust searching ability encompasses the exploitation and exploration of the search space [75]. This exploitation process is performed during the employed and onlooker bee phase, while during the scout bee phase the exploration process is accomplished. The overall ABC optimization process is illustrated by the flow chart given in Fig. 4.2.

![Flowchart of the ABC optimization approach.](image)

**Figure 4.2:** Flowchart of the ABC optimization approach.
4.4 Optimization and proposed approach

There is only one employed bee for every food source. By using the following expression, each employed bee moves from one old location $x_{ij}$ to a new candidate location $v_{ij}$:

$$v_{ij} = x_{ij} + \phi_{ij} (x_{ij} - x_{kj})$$  (4.27)

In (4.27), $k \in 1, 2, ..., SN$ and $j \in 1, 2, ..., D$ are randomly chosen and $k$ has to be different from $i$, where, $SN =$ the number of food sources, $D =$ problem dimension, and $\phi_{ij} =$ uniform random number in the range [-1, 1]. If the new location value $v_{ij}$ is better than $x_{ij}$, then $x_{ij}$ is updated and replaced with $v_{ij}$, otherwise $x_{ij}$ is kept unchanged. Depending on the probability value, the onlooker bee selects a food source by using a roulette wheel selection method and this new position is then determined by (4.28), where, $\omega_i =$ weight coefficient of employed bee information.

$$v_{ij} = x_{ij} + \omega_i \phi_{ij} (x_{ij} - x_{kj})$$  (4.28)

The food source probability ($p_i$) and the fitness values of the food sources of employed bees ($fit$) are calculated according to (4.29) and (4.30), respectively, where, $f(x_i)$ denotes the number of objective function values to be optimized.

$$p_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j}$$  (4.29)

$$fit_i = \begin{cases} \frac{1}{1 + f(x_i)}, & f(x_i) \geq 0 \\ 1 + |f(x_i)|, & f(x_i) < 0 \end{cases}$$  (4.30)

4.4.2 Proposed approach

The proposed methodology for resolving the optimal distributed ESS placement problem is represented in Fig. 4.3. The optimization parameters and variables are summarized in Table 4.1. After modeling, configuring, and placing all required components in the distribution system of Fig. 4.1, all the essential system data are entered in the corresponding components and the ABC parameters are initialized. The ABC parameters are determined according to the system requirements as given in Table 4.1 which indicates that the population size is 50 and the simulation is conducted for total of 1000 iterations with a trial limit of 60 to determine two decision variables $S_{ESS}^i$ and $\lambda_{ESS}^i$. 
The total active and reactive powers for the feeder \((P_{TF} \& Q_{TF})\) are entered for feeder load scaling and the operational capacity of solar DGs \((S_{pv-op})\) is considered as 85% of rated capacity \((S_{pv-max})\) [77]. Subsequently, the loads, solar, and wind DGs are characterized by applying time-variant characteristics [12]. The feeder loads are scaled by creating voltage dependency. Then the problem is formulated to minimize the total of \(C_{VD}, C_{PL}, C_{LL},\) and \(C_{UT, ESS}^I\).

![Flowchart of the proposed optimal distributed ESS placement approach.](Image)

**Figure 4.3:** Flowchart of the proposed optimal distributed ESS placement approach.

The investigations are accomplished in two phases- (1) Investigation type-I: with a uniform ESS size and (2) Investigation type-II: with non-uniform ESS sizes. The ESS
### 4.5 Testing and performance measurement

<table>
<thead>
<tr>
<th>Type</th>
<th>Parameters/variables</th>
<th>Description/settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input parameters</td>
<td>$V_{\text{rated}}$, $R_L(i,j)$, $X_L(i,j)$, $P$, $Q$, $P_{TF}$, $Q_{TF}$, $S_{\text{wind}}$, $S_{PV-max}$, $S_{PV-op}$, and $S_{\text{ESS-max}}$</td>
<td>Required for the network model.</td>
</tr>
<tr>
<td>Output parameters</td>
<td>$C_{VD}$, $C_{PL}$, $C_{LL}$, and $C_{UT}^{ESS}$</td>
<td>Required for the objective function.</td>
</tr>
<tr>
<td>Decision variables</td>
<td>$S_{\text{ESS}}$</td>
<td>Determines the ESS size in MVA with unity power factor, i.e., the ESSs inject only $P$ (MW) to the network ($Q = 0$).</td>
</tr>
<tr>
<td></td>
<td>$\lambda_{\text{ESS}}$</td>
<td>This determines the ESS position in the network.</td>
</tr>
<tr>
<td>ABC parameters</td>
<td>$N_D$, $CS$, $N_{FS}$, $L_{trial}$, and $I_{max}$</td>
<td>Settings: $N_D = 2$, $CS = 100$, $N_{FS} = CS/2$ = population size, $L_{trial} = 60$, and $I_{max} = 1000$.</td>
</tr>
<tr>
<td>ABC bounds</td>
<td>For $S_{\text{ESS}}$: $lb1$ and $ub1$</td>
<td>Settings: $lb1 = 0.1$ MVA and $ub1 = 2$ MVA.</td>
</tr>
<tr>
<td></td>
<td>For $\lambda_{\text{ESS}}$: $lb2$ and $ub2$</td>
<td>Settings: $lb2 = 0$ and $ub2 = 1$.</td>
</tr>
</tbody>
</table>

Table 4.1: Summary of ABC optimization parameters and variables

The size ($S_{\text{ESS}}^i$) and positions ($\lambda_{\text{ESS}}^i$) are generated randomly and applied to the system. The $S_{\text{ESS}}^i$ is generated in such a way that the maximum number of ESSs with lower capacity (within the range 0.1 MVA to 2 MVA) can be distributed in the network. The initial values are selected randomly by relying on the nominated range of sizes to be tested on the network. The ESS size nomination is subject to $lb1$, $ub1$, $lb2$, $ub2$, transformer size, DC and AC bus size, inverter specifications, and ESS string size. Finally, the ABC optimization process finds the optimal values of $S_{\text{ESS}}^i$ and $\lambda_{\text{ESS}}^i$ by satisfying the objective function constraints.

In this research, the sizing approach considers a unity power factor applied on the dispatch of ESSs. This is based on common industry practices that distribution network operators will not rely on the distributed generators to solve the network voltage problem, but rather rely on the substation automatic voltage controllers and distributed capacitors to control the MVars. Hence, the ESS size and locations are determined based on using the multi-functionality of ESSs in providing the MW required to minimize line losses and loading, and support the voltage controllers on the network. This approach maintains the voltage at the desired levels proposed by operation requirements.

### 4.5 Testing and performance measurement

This section describes the application of necessary factors of load model and RES generation, feeder load scaling, and voltage dependency in the proposed distribution
4. OPTIMAL ESS PLACEMENT AND SIZING IN DISTRIBUTION NETWORKS USING P INJECTION APPROACH

network model. Furthermore, it states the essential indices to measure the performance improvement of the system.

4.5.1 Assignment of factors and dependency

4.5.1.1 Feeder load scaling and voltage dependency

Considering the scaling factor, the load is calculated according to (4.31) and (4.32) [78]. The load scaling of a distribution feeder, consisting of loads \( \text{Load}_i \), is presented in Fig. 4.4. The \( \Psi_{scale} \) is adjusted so that the total real and reactive powers are calculated as (4.33) and (4.34), respectively [78].

\[
P = \Psi_{scale} \cdot P_0 \tag{4.31}
\]

\[
Q = \Psi_{scale} \cdot Q_0 \tag{4.32}
\]

\[
P = \Psi_{scale} \cdot P_1 + \Psi_{scale} \cdot P_2 + \Psi_{scale} \cdot P_3 + \ldots + \Psi_{scale} \cdot P_n \tag{4.33}
\]

\[
Q = \Psi_{scale} \cdot Q_1 + \Psi_{scale} \cdot Q_2 + \Psi_{scale} \cdot Q_3 + \ldots + \Psi_{scale} \cdot Q_n \tag{4.34}
\]

Taking into account the voltage dependency of loads, (4.31) and (4.32) are converted to (4.35) and (4.36), respectively, where, \((1 - aP - bP) = cP\) and \((1 - aQ - bQ) = cQ\).

\[
P = \Psi_{scale} \cdot P_0 \left[ aP \cdot \left( \frac{V_{bi}}{V_{ref}} \right)^{\epsilon_{aP}} + bP \cdot \left( \frac{V_{bi}}{V_{ref}} \right)^{\epsilon_{bP}} \right] + (1 - aP - bP) \cdot \left( \frac{V_{bi}}{V_{ref}} \right)^{\epsilon_{P}} \tag{4.35}
\]

\[
Q = \Psi_{scale} \cdot Q_0 \left[ aQ \cdot \left( \frac{V_{bi}}{V_{ref}} \right)^{\epsilon_{aQ}} + bQ \cdot \left( \frac{V_{bi}}{V_{ref}} \right)^{\epsilon_{bQ}} \right] + (1 - aQ - bQ) \cdot \left( \frac{V_{bi}}{V_{ref}} \right)^{\epsilon_{Q}} \tag{4.36}
\]
4.5 Testing and performance measurement

Figure 4.4: Load scaling of a distribution feeder [78].

4.5.1.2 Load and generation scaling factors

The loads of the distribution network follow the IEEE-RTS model as depicted in Fig. 4.5 and the load coefficients are set to $aP = aQ = 0.4$, $bP = bQ = 0.3$, and $cP = cQ = 0.3$ [12]. The exponents are assigned to $e_aP = e_aQ = 0$, $e_bP = e_bQ = 1$, and $e_cP = e_cQ = 2$ to model the load behaviour as constant power, constant current, and constant impedance, respectively, for corresponding load coefficients [78]. The generation outputs of solar PV and wind DGs are scaled according to the curves of Fig. 4.5 [12].

4.5.2 System performance indices

4.5.2.1 Voltage deviation and profile improvement indices

As the minimization of voltage fluctuations is crucial for the operation of the power systems, the permissible voltage deviation limit is considered as ±5% in this research. The voltage deviation index ($VDI$) of (4.37), expressed as a percentage, represents the system voltage deviation [79].

$$\% \ VDI = \sum_{i=1}^{N} \left( \frac{|V_{rated} - V_{bi}|}{V_{rated}} \right) \times 100 \quad (4.37)$$

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The voltage profile of the system can be defined as (4.38). The and for the system are determined by the voltage violation limit (±5%).

\[ VP_i = V_{bi} S_{Li} \zeta_i \quad (4.38) \]

The incorporation of a load weighting factor has considerable impact on the voltage profile improvement index (VPII), which allows the possibility of a low load bus with voltage sensitive loads. Generally, these factors are assigned based on the criticality or importance of the load at each bus. It is assumed that all the loads of the proposed system have equal importance. For the overall network, the total of all factors is defined as (4.39).

\[ \sum_{i=1}^{N} \zeta_i = 1 \quad (4.39) \]

Hence, the overall voltage profile of the system can be expressed as (4.40).

\[ VP = \sum_{i=1}^{N} VP_i \quad (4.40) \]
4.5 Testing and performance measurement

The $VPII$, a measure of the improved voltage profile of the proposed distribution system, can be defined as (4.41) [80].

$$VPII = \frac{VP_{w-ESS}}{VP_{w0-ESS}}$$  \hspace{1cm} (4.41)

### 4.5.2.2 Power loss reduction indices

The real, reactive, and total power loss reduction indices ($PLRI_P$, $PLRI_Q$, and $PLRI_T$) are defined by (4.42), (4.43), and (4.44), respectively [79, 80].

$$PLRI_P = \frac{\sum_{l=1}^{M} P_{L-ESS}^l}{\sum_{l=1}^{M} P_{L-base}^l}$$  \hspace{1cm} (4.42)

$$PLRI_Q = \frac{\sum_{l=1}^{M} Q_{L-ESS}^l}{\sum_{l=1}^{M} Q_{L-base}^l}$$  \hspace{1cm} (4.43)

$$PLRI_T = \frac{\sum_{l=1}^{M} \sqrt{(P_{L-ESS}^l)^2 + (Q_{L-ESS}^l)^2}}{\sum_{l=1}^{M} \sqrt{(P_{L-base}^l)^2 + (Q_{L-base}^l)^2}}$$  \hspace{1cm} (4.44)

### 4.5.2.3 Line loading index:

The line loading index ($LLI$) refers to the loading level or demand of the distribution system lines. Minimizing line loading through optimally placed ESSs may be an effective way of deferring distribution investment. In other words, the distribution network peak demand can be reduced by minimizing the $LLI$. This may also minimize the investment costs for distribution network expansion. This is necessary in order to increase the system’s tolerance of load growth. In this research, the percent line loading ($\%LL$) for a specific line, total percent line loading ($\%LLT$) (before and after ESS placement), and the overall $LLI$ are formulated by (4.14) and (4.45) to (4.48).

$$\%LL_{base} = \left( \frac{SL_{base}^l}{SL_{rated}^l} \right) \times 100$$  \hspace{1cm} (4.45)

$$\%LL_{w-ESS} = \sum_{l=1}^{M} \%LL_{ESS}$$  \hspace{1cm} (4.46)
4. OPTIMAL ESS PLACEMENT AND SIZING IN DISTRIBUTION NETWORKS USING P INJECTION APPROACH

\[
\% \text{LLT}_{\text{wo}-\text{ESS}} = \sum_{l=1}^{M} \% \text{LL}_{\text{base}} \tag{4.47}
\]

\[
\text{LLI} = \frac{\% \text{LLT}_{w-\text{ESS}}}{\% \text{LLT}_{\text{wo}-\text{ESS}}} \tag{4.48}
\]

4.6 Results and discussion

After optimization and testing, the system performance is analyzed in three different case studies. Optimal ESS locations are determined while minimizing the cost function. This section describes the impact of optimal distributed ESS allocation in the proposed distribution system. The ESSs only inject P (MW) to the network and the power factor is unity. The system results are categorized for three cases: base case (without ESS), ESS placement while considering a uniform ESS size, and non-uniform ESS sizes. These are presented in Table 4.2. The investigation is conducted for a time period of 24 hours and the maximum value of parameters %VDI, %LLT, P_T, and Q_T for that period is calculated. Case 2 and Case 3 are investigated in two different subcategories based on the weighting factor selection of \( J(C_{F_1}) \) as given in Table 4.2. Although the factors in (4.8) are equally weighted (Case 2(I) and Case 3(I)), \( \gamma_{VD} \) is changed to 100 along with \( \gamma_{PL} = \gamma_{LL} = \gamma_{ESS} = 1 \) in Case 2(II) and Case 3(II) to give more importance to \( C^n_{VD} \) than other parameters. This comparison is presented targeting better realization of the optimization results. It is assumed that the ESS power rating (MVA) is constant over one hour.

4.6.1 Case study 1- Base case without ESSs

The results of parameter %VDI, %LLT, P_T, and Q_T for base case analysis (without the placement of ESSs), tabulated in Table 4.2 represent the reference values which are targeted to be optimized. Although the \( V_{bi} \) is within maximum and minimum voltage limits, the voltage profile needs improvement. Similar results are observed for other parameter values.
### 4.6 Results and discussion

#### Table 4.2: System results after a quantitative analysis

<table>
<thead>
<tr>
<th>Case Details</th>
<th>ESS Apparent Power (MVA) &amp; Locations</th>
<th>%VDI</th>
<th>%LLT</th>
<th>$P_T$ (MW)</th>
<th>$Q_T$ (MVar)</th>
<th>Total ESS Size (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Case 1</strong></td>
<td>Without ESS allocation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base case</td>
<td>No ESS</td>
<td>89.73</td>
<td>269.81</td>
<td>0.11</td>
<td>0.09</td>
<td>-</td>
</tr>
<tr>
<td><strong>Case 2</strong></td>
<td>Distributed ESS allocation for a uniform ESS size</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(I). Min $J(C_{pi})$ with $\gamma_{VD} = \gamma_{PL} = \gamma_{LL} = \gamma_{ESS} = 1$</td>
<td>ESS9, ESS14, ESS25, ESS28, ESS29, ESS30, ESS31, ESS32, ESS MVA=0.724</td>
<td>75.753</td>
<td>241.128</td>
<td>0.0905</td>
<td>0.0683</td>
<td>5.793</td>
</tr>
<tr>
<td>(II). Min $J(C_{pi})$ with $\gamma_{VD} = 100$ &amp; $\gamma_{PL} = \gamma_{LL} = \gamma_{ESS} = 1$</td>
<td>ESS9, ESS11, ESS14, ESS15, ESS25, ESS27, ESS28, ESS29, ESS30, ESS31, ESS32, ESS33, ESS MVA=1.974</td>
<td>32.238</td>
<td>440.955</td>
<td>0.2491</td>
<td>0.2691</td>
<td>23.689</td>
</tr>
<tr>
<td><strong>Case 3</strong></td>
<td>Distributed ESS allocation for non-uniform ESS sizes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(I). Min $J(C_{pi})$ with $\gamma_{VD} = \gamma_{PL} = \gamma_{LL} = \gamma_{ESS} = 1$</td>
<td>ESS9=0.335, ESS10=0.378, ESS13=0.381, ESS16=0.823, ESS17=0.1, ESS20=0.128, ESS22=0.1, ESS25=2, ESS30=1.442, ESS31=0.725, ESS32=0.781</td>
<td>72.162</td>
<td>240.039</td>
<td>0.0894</td>
<td>0.0666</td>
<td>7.195</td>
</tr>
<tr>
<td>(II). Min $J(C_{pi})$ with $\gamma_{VD} = 100$ &amp; $\gamma_{PL} = \gamma_{LL} = \gamma_{ESS} = 1$</td>
<td>ESS9=0.28, ESS11=1.13, ESS13=0.454, ESS14=1.42, ESS15=0.735, ESS17=2, ESS25=2, ESS26=0.11, ESS27=0.711, ESS28=1.427, ESS29=2, ESS30=2, ESS31=1.873, ESS32=1.603, ESS33=0.682</td>
<td>41.520</td>
<td>388.220</td>
<td>0.1830</td>
<td>0.2100</td>
<td>18.425</td>
</tr>
</tbody>
</table>

#### 4.6.2 Case study 2- ESS allocation for a uniform ESS size

Case 2, optimal ESS placement for a uniform $S_{ESS}^i$, is divided into two different categories with two different combinations of $S_{ESS}^i$ and $\lambda_{ESS}^i$. The $S_{ESS}^i$ and $\lambda_{ESS}^i$ can be identified in Table 4.2 by the ESS MVA and ESS number, respectively: e.g., ESS9 = 0.724 represents that the ESS of size 0.724 MVA is connected to bus9. It is noticeable that all Case 2(I) parameters (%VDI, %LLT, $P_T$, and $Q_T$) are minimized compared to Case 1. Although Case 2(II) minimizes the $C_{VD}^n$ — i.e. improves the voltage profile (%VDI = 32.238) — the %LLT, $P_T$, and $Q_T$ exceed the corresponding values for Case 1. Furthermore, the total ESS size is 23.689 MWh, which represents a higher distribution system investment cost and hence is unacceptable. For Case 2(I), the required number of optimally placed ESSs in the network is 8 with $S_{ESS}^i = 0.724$ MVA, while it is 12 with $S_{ESS}^i = 1.974$ MVA for Case2(II). Hence, considering the optimal performance as well as costs and a negotiation of %VDI, Case 2(I) is the required optimal solution with minimum ESS size (5.793 MWh) for Investigation type-I.
4. OPTIMAL ESS PLACEMENT AND SIZING IN DISTRIBUTION NETWORKS USING P INJECTION APPROACH

4.6.3 Case study 3- ESS allocation for non-uniform ESS sizes

The impact of optimal distributed ESS allocation with non-uniform $S^i_{ESS}$ is analyzed and the results are listed in Table 4.2. Case 3(I) shows the optimization results with minimum $J(C_{F_i})$, while Case 3(II) represents the outcome for minimum $C^o_{VD}$. A very noticeable point is that all the parameters (%VDI, %LLT, $P_T$, and $Q_T$) are further reduced compared to Case 2(I). However, for Case 3(I), the required number of optimally placed ESSs is 11 and total ESS size is 7.195 MWh, which represents an increment in cost over Case 2(I). The total ESS size is further increased to 18.425 MWh while minimizing $C^o_{VD}$ (%VDI=41.520) in Case 3(II). For this case, the other parameters (%LLT, $P_T$, and $Q_T$) are higher compared to Case 2(I) and Case 3(I).

4.6.4 Overall result comparison and analysis

![Voltage profiles for various cases.](image)

**Figure 4.6**: Voltage profiles for various cases.

4.6.4.1 Comparison of voltage profiles

The voltage profiles for various cases are depicted in Fig. 4.6. The feeder voltage profiles (p.u. voltage vs km) after ESS placement, i.e. for Case 2 and Case 3 of Table 4.2, are illustrated in Fig. 4.7 to Fig. 4.10, where various sections in terms of feeder
4.6 Results and discussion

Figure 4.7: Voltage profile of the feeder for case 2(I).

Figure 4.8: Voltage profile of the feeder for case 2(II).

length are marked with different colors. In the distribution network model, all the lines have the same length (1km). At some buses, the p.u. voltages for the particular
feeder length are illustrated. According to Fig. 4.7 and Fig. 4.6, the bus voltages vary within 1 p.u. to 0.967 p.u. for Case 2(I), while the lowest voltage value (0.967 p.u.) is observed at B30. B18 and B33 have about the same voltage of 0.973 p.u, while the similar voltage value of around 0.972 p.u. is obtained at B16 and B31. Case
3(I) has a better feeder voltage profile compared to Case 2(I) as presented in Fig. 4.9 and Fig. 4.6. The voltages at various bus during Case 3(I) are improved, e.g., at B16 (Case 3(I)=0.976 p.u., Case 2(I)=0.972 p.u.), at B31 & B32 (Case 3(I)=0.975 p.u., Case 2(I)=0.972 p.u.), and at B33 (Case 3(I)=0.976 p.u., Case 2(I)=0.973 p.u.). The Case 2(II) provides the best voltage profile compared to other cases as per Fig. 4.6 to Fig. 4.10. During this case, most of the bus voltages vary around the target voltage 1 p.u. as presented in Fig. 4.8, while the lowest voltage of 0.97 p.u. is observed at B24. The voltages at some buses, e.g., B09, B15, and B14 are above the $V_{\text{target}}$. On the other hand, Case 3(II) also provides an improver voltage profile than Case 2(I) and Case 3(I). However, there are higher voltage drops at some buses compared to Case 2(II) such as at B6 (Case 3(II)=0.978 p.u., Case 2(II)=0.981 p.u.), B8 (Case 3(II)=0.980 p.u., Case 2(II)=0.987 p.u.), B12 (Case 3(II)=0.985 p.u., Case 2(II)=0.997 p.u.), B20 (Case 3(II)=0.986 p.u., Case 2(II)=0.992 p.u.), B21(Case 3(II)=0.985 p.u., Case 2(II)=0.993 p.u.), and B27 (Case 3(II)=0.981 p.u., Case 2(II)=0.985 p.u.). There are also improvements on voltages at some buses in Case 3(II) compared to Case 2(II), for instance, at B17 (Case 3(II)=1.002 p.u., Case 2(II)=0.997 p.u.), B18 (Case 3(II)=1.001 p.u., Case 2(II)=0.999 p.u.), B25 (Case 3(II)=0.983 p.u., Case 2(II)=0.976 p.u.), and B33 (Case 3(II)=1.001 p.u., Case 2(II)=0.998 p.u.).

It may also be noted that the voltage drop in the feeder section numbered L02-L22-L23-L24-L37-L29-L30 is higher for Case 2(I), Case 2(II), and Case 3(I) compared to other sections of Fig. 4.1, and there is an improvement in this characteristic for Case 3(II). In contrast, the voltage drop in the feeder section numbered L18-L19-L20-L21-L35 is lower than other sections for all cases except Case 2(I) where the voltage drop in L20 is slightly higher compared to other cases. Case 2(II) provides an improved feeder voltage profile compared to Case 3(II) and most of the bus voltages are very close to 1 p.u. for Case 2(II) except B07, B23, B24, B25, B29, and B30. The voltages of these buses are further improved (except B07) in Case 3(II) while having little voltage deviation in other buses compared to Case 2(II). Hence, it is evident that Case 2(II) and Case 3(II) have better voltage profiles among the options, while Case 2(I) and Case 3(I) provide good voltage profiles.
4.6.4.2 Comparison of line loading and losses

The percent line loadings of various cases are presented in Fig. 4.11. This suggests that the loading of lines for each case is under the maximum limit. For Case 2(II) and Case 3(II) the line loadings are higher, while Case 2(II) provides the worst loading in lines especially in L8, L22, L26, L28, L30, L35, and L37. Case 2(I) and Case 3(I) have good line loading among the options, while the best characteristics are provided by Case 3(I). Although the maximum loading limit of a line is 80%, L1 has maximum loading of 40.801% for all cases. L2 has around 28% loading for Case 1, Case 3(I), and Case 3(II), while it has a lower (27.633%) and a higher (31.908%) loading value for Case 2(I) and Case 2(II), respectively. All other lines for most of the cases are more lightly loaded (below 15%) except L30 and L37. For Case 2(II), the L30 and L37 are loaded around 27%, while L37 in Case 3(II) is loaded about 22%. It can be noted from the line loading characteristics that the overall feeder has sufficient spare capacity to tackle the worst situation during outage condition by sharing the loads with others.

Figure 4.11: The percent line loading for various cases.

The real, reactive, and total power losses of lines for various cases, with respect to individual line numbers, are compared in Fig. 4.12, Fig. 4.13, and Fig. 4.14, respectively. According to Fig. 4.12, L2 has a real power loss of 0.0347 MW, 0.0271 MW, and 0.0269
4.6 Results and discussion

**Figure 4.12:** Real power loss for various cases.

**Figure 4.13:** Reactive power loss for various cases.

MW for Case 2(II), Case 3(I), and Case 3(II), respectively. Case 2(II) and 3(II) provide higher real power losses (compared to other cases) in L30 which are 0.0513 MW and 0.0387 MW, respectively. The L8 has a real power loss of 0.0424MW for Case 2(II) which is higher than other cases. It is also noticeable for all cases that there is no real
power loss in tie lines (L33 to L37) as illustrated in Fig. 4.12. As referred to Fig. 4.13, higher reactive power loss is delivered during Case 2(II) compared to other cases, specifically in L2, L8, L30, L35, and L37. In L2, Case 2(I), Case 3(I), and Case 3(II) have the similar amount of reactive power loss which is 0.0133 MVar, 0.0138 MVar, and 0.0137 MVar, respectively, while it is a bit higher (0.0177 MVar) for Case 2(II). In L8, Case 2(II) and Case 3(II) have a higher reactive power loss of 0.0305 MVar and 0.0088 MVar, respectively. Case 3(II) gives the highest reactive power loss of 0.0190 MVar and 0.0112 MVar in L16 and L24, respectively. In L30, Case 2(II) has the highest reactive power loss of 0.0507 MVar compared to all other lines. Remarkably, all cases provide reactive power loss to the tie lines (L33 to L37), while higher losses are added by Case 2(II) and Case 3(II) compared to others. Overall, according to the illustrations of Fig. 4.12, Fig. 4.13, and Fig. 4.14, the losses are higher for Case 2(II) and Case 3(II) and lower for Case 2(I) and Case 3(I). Again, the worst case for total line loss is Case 2(II), while having larger amount of loss in L2, L8, L30, L35, and L37 compared to other cases.

4.6.4.3 Statistical analysis of ABC approach with PSO algorithm

The well-known PSO algorithm [81, 82] is employed to verify the ESS allocation results of Case 2(I) and Case 3(I) obtained from the ABC approach. The PSO algorithm
4.6 Results and discussion

used in this study is given below:

\[ v_i^{PSO}(k + 1) = w^{PSO} \cdot v_i^{PSO}(k) + c_1 r_1 \cdot (p_{BEST_i} - x_i^{PSO}(k)) + c_2 r_2 \cdot (g_{BEST_i} - x_i^{PSO}(k)); \]  \hfill (4.49)

\[ x_i^{PSO}(k + 1) = x_i^{PSO}(k) + v_i^{PSO}(k + 1); \]  \hfill (4.50)

where, \( i = 1, 2, \ldots, N \), \( v_i^{PSO} \) and \( x_i^{PSO} \) = the velocity and position of \( i \)th particle, \( p_{BEST_i} \) = best solution determined by a particle itself, \( g_{BEST_i} \) = best solution in the neighbourhood, \( k \) = iteration number, \( w^{PSO} \) = inertia weight, \( r_1 \) and \( r_2 \) = random variables in the range \([0,1]\), and \( c_1 \) and \( c_2 \) = the cognitive and social components. The initial condition regarding the objective function for PSO (\( J(C_{Fi})^{PSO} \)) is defined in (4.52). If (4.52) is satisfied, the \( p_{BEST_i} \) is updated using (4.51).

\[ p_{BEST_i} = x_{ik}^{PSO} \]  \hfill (4.51)

\[ J(C_{Fi})^{PSO}(x_{ik}^{PSO}) > J(C_{Fi})^{PSO}(p_{BEST_i}) \]  \hfill (4.52)

The work flow of the PSO algorithm can be described in five following essential steps:

- **Step 1**: Initializing the \( v_i^{PSO} \) and \( x_i^{PSO} \) randomly.
- **Step 2**: Evaluating the objective function \( J(C_{Fi})^{PSO} \).
- **Step 3**: Evaluating \( p_{BEST_i} \) and \( g_{BEST_i} \).
- **Step 4**: Updating the \( v_i^{PSO} \) and \( x_i^{PSO} \).
- **Step 5**: Repeating steps 2 to 4 until the optimization criteria are met.

Cognitive and social components (\( c_1 \) and \( c_2 \)) of PSO are both set to 1.8, while the inertia weight (\( w^{PSO} \)) is selected as 0.6 as recommended in [55]. The ABC settings are listed in Table 4.1. The ABC optimization and the PSO are executed for 30 times considering a maximum iteration value of 1000, a population size of 50, and \( \gamma_{VD} = \gamma_{PL} = \gamma_{LL} = \gamma_{ESS} = 1 \) in (4.8). From the list of obtained results, the best, worst, and mean objective function solutions are compared in Table 4.3 for the two investigation types. Furthermore, the standard deviations for ABC and PSO approaches (\( \sigma_{ABC} \) and \( \sigma_{PSO} \)) of objective function values are evaluated. The lesser standard deviation value represents smaller
4. OPTIMAL ESS PLACEMENT AND SIZING IN DISTRIBUTION NETWORKS USING P INJECTION APPROACH

### Table 4.3: Statistical analysis of ABC and PSO approaches for 30 runs

<table>
<thead>
<tr>
<th>Investigation Type</th>
<th>ESS Apparent Power (MVA) Locations</th>
<th>Objective Function Value ($)</th>
<th>ESS Apparent Power (MVA)</th>
<th>Total ESS Size (MWh)</th>
<th>(%) VDI</th>
<th>(%) LTC</th>
<th>Total ESS Size (MWh)</th>
<th>(%) VDI</th>
<th>(%) LTC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type-I: Distributed ESS allocation for a uniform ESS size</td>
<td>ABC best</td>
<td>ESS9, ESS14, ESS25, ESS28, ESS29, ESS30, ESS31, ESS32</td>
<td>0.724</td>
<td>0.75753</td>
<td>241.128</td>
<td>0.0905</td>
<td>0.0683</td>
<td>5.793</td>
<td>26,65,008.853</td>
</tr>
<tr>
<td></td>
<td>ABC worst</td>
<td>ESS7, ESS13, ESS15, ESS25, ESS28, ESS29, ESS30, ESS31, ESS32</td>
<td>0.667</td>
<td>0.77534</td>
<td>242.162</td>
<td>0.0909</td>
<td>0.0684</td>
<td>6.000</td>
<td>27,60,040.417</td>
</tr>
<tr>
<td></td>
<td>ABC mean</td>
<td>ESS7, ESS9, ESS15, ESS25, ESS29, ESS30, ESS31, ESS32</td>
<td>0.747</td>
<td>0.76967</td>
<td>241.642</td>
<td>0.0918</td>
<td>0.0677</td>
<td>5.972</td>
<td>27,47,375.519</td>
</tr>
<tr>
<td></td>
<td>(\sigma_{ABC})</td>
<td></td>
<td></td>
<td>16374.188</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Type-II: Distributed ESS allocation for non-uniform ESS sizes</td>
<td>ABC best</td>
<td>ESS8=0.335, ESS10=0.378, ESS13=0.383, ESS16=0.823, ESS17=0.1, ESS20=0.128, ESS22=0.1, ESS25=2, ESS30=1.442, ESS31=0.725, ESS32=0.781</td>
<td>0.724</td>
<td>0.72162</td>
<td>240.039</td>
<td>0.0894</td>
<td>0.0666</td>
<td>7.195</td>
<td>33,09,852.689</td>
</tr>
<tr>
<td></td>
<td>ABC worst</td>
<td>ESS5=0.1, ESS9=0.556, ESS11=0.1, ESS15=0.836, ESS17=0.1, ESS22=0.1, ESS24=0.1, ESS25=1.479, ESS26=0.164, ESS28=0.1, ESS30=2.0, ESS31=1.589, ESS33=0.121</td>
<td>0.724</td>
<td>0.72623</td>
<td>243.322</td>
<td>0.0889</td>
<td>0.0678</td>
<td>7.345</td>
<td>33,78,653.069</td>
</tr>
<tr>
<td></td>
<td>ABC mean</td>
<td>ESS8=0.162, ESS10=0.181, ESS13=0.237, ESS15=0.512, ESS21=0.1, ESS24=0.101, ESS25=1.736, ESS26=0.310, ESS28=0.159, ESS30=2.0, ESS31=0.492, ESS32=1.226</td>
<td>0.724</td>
<td>0.73954</td>
<td>241.143</td>
<td>0.0867</td>
<td>0.0679</td>
<td>7.216</td>
<td>33,19,390.463</td>
</tr>
<tr>
<td></td>
<td>(\sigma_{ABC})</td>
<td></td>
<td></td>
<td>12939.034</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
4.6 Results and discussion

Table 4.4: Convergence and computation time of ABC and PSO algorithms

<table>
<thead>
<tr>
<th>Investigation type</th>
<th>ABC convergence</th>
<th>ABC computation time (s)</th>
<th>PSO convergence</th>
<th>PSO computation time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>After 208 iterations</td>
<td>325</td>
<td>After 191 iterations</td>
<td>440</td>
</tr>
<tr>
<td>II</td>
<td>After 347 iterations</td>
<td>503</td>
<td>After 332 iterations</td>
<td>665</td>
</tr>
</tbody>
</table>

deviation among solutions of 30 times optimization runs. Although both algorithms provide very close solutions in terms of objective function costs, it is evident from Table 4.3 that the more optimal solutions are obtained from the ABC for both investigation types. For instance, the ABC best solution for investigation type-I signifies the improvement in performance such as \( \%VDI = 75.753 \), \( \%LLT = 241.128 \), \( P_T = 0.0905 \) MW, and total ESS size (5.793 MWh) except little deviation in \( Q_T \) (0.0683 MVar) compared to PSO best solution (i.e. \( VDI = 76.894 \), \( LLT = 241.633 \), \( P_T = 0.0917 \) MW, \( Q_T = 0.0677 \) MVar, and total ESS size=6.007 MWh). Hence, it is obvious from the statistical analysis of Table 4.3 that the proposed ABC-based approach is successful in achieving required optimal solutions for both investigation types.

![Figure 4.15: Convergence of ABC and PSO algorithms.](image)

The configuration of the used computer for conducting the optimization is: Intel(R) Xeon 3.5 GHz processor, 16 GB RAM, 64-bit windows 10. Fig. 4.15 represents the
convergence test of the ABC and PSO algorithms for two investigation types. The convergence results and computation time are summarized in Table 4.4. This suggests that the ABC-based approach converges after 208 and 347 iterations for investigation type-I and investigation type-II, respectively. On the contrary, PSO algorithm converges after 191 and 332 iterations for investigation type-I and investigation type-II, respectively. In other words, the PSO algorithm converges faster than the ABC approach. In real time, ABC and PSO algorithms require around 325 s and 440 s, respectively, to locate the ESSs under investigation type-I. For investigation type-II, the ABC and PSO approaches take about 503 s and 665 s, respectively, to place the ESSs on the network.

4.6.4.4 Overall performance and ESS cost comparison

The performance indices of the proposed system are evaluated and presented in Table 4.5. Generally, the system has a good voltage profile for \( VPII > 1 \). For instance, the \( VPII = 2.114 \) for Case 2(II) represents that Case 2(II) has the best voltage profile among the options. On the other hand, the higher values of \( PLRI_P, PLRI_Q, PLRI_T, \) and \( LLI \) denote higher real power loss, reactive power loss, total line loss, and line loading, respectively. For example, Case 3(I) has the \( PLRI_T = 0.802 \) and the \( LLI = 0.890 \) which are lower than those of Case 2(I) \( (PLRI_T = 0.816 \& LLI = 0.894) \). This implies that Case 3(I) has achieved improved performance in regard to total line loss and line loading compared to Case 2(I).

<table>
<thead>
<tr>
<th>Case Details</th>
<th>( VPII )</th>
<th>( PLRI_P )</th>
<th>( PLRI_Q )</th>
<th>( PLRI_T )</th>
<th>( LLI )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Case 2(I)</td>
<td>1.037</td>
<td>0.829</td>
<td>0.802</td>
<td>0.816</td>
<td>0.894</td>
</tr>
<tr>
<td>Case 2(II)</td>
<td>2.114</td>
<td>2.281</td>
<td>3.158</td>
<td>2.755</td>
<td>1.634</td>
</tr>
<tr>
<td>Case 3(I)</td>
<td>1.064</td>
<td>0.819</td>
<td>0.781</td>
<td>0.802</td>
<td>0.890</td>
</tr>
<tr>
<td>Case 3(II)</td>
<td>1.823</td>
<td>1.675</td>
<td>2.408</td>
<td>2.059</td>
<td>1.439</td>
</tr>
</tbody>
</table>

Fig. 4.16 presents the overall comparison of the system performance indices and total ESS unit cost (as the total ESS unit cost is the highest cost component of the system, which is defined in (4.15)). It is apparent from the characteristics that case 2(I) is relatively cost efficient and is the optimal solution for distributed ESS allocation with
a uniform size, while Case 3(I) is the optimal choice for ESS allocation with non-uniform sizes.

4.7 Conclusions

This chapter has presented an effective strategy for the optimal placement of distributed ESSs in distribution networks using the ABC meta-heuristic optimization technique. The key problems of voltage deviation, line loading, and power losses in distribution networks are addressed and mitigated to improve system performance. The PSO algorithm is also applied to verify the system results obtained from the ABC approach. The related performance indices are evaluated and overall system results are analyzed quantitatively. Based on the investigations and analysis presented in this study, the following conclusions can be made in regard to optimal ESS placement:

- The optimal placement of multiple ESSs, in a distributed manner, offers good flexibility and performance improvement in a distribution network with large renewable DG penetration.
Both approaches – optimal distributed ESS placement with a uniform size and non-uniform sizes – are suitable for solving distribution network issues as addressed in this research. However, ESS placement with a uniform size technique can be implemented more flexibly, while the approach with non-uniform ESS sizes is more adjustable with regard to performance improvement.

As the optimal ESS placement largely depends on performance improvement targets, a tradeoff should be made in terms of performance indices, installation sites, and costs. For instance, considering optimal performance as well as implementation costs, and a tradeoff with voltage profile, line loading, and losses, Case 2(1) presented in Section VI is the optimal solution.

Overall, considering the above findings, the proposed approach for optimal placement of distributed ESSs is highly suitable for an MV or large-scale distribution system and can be used in real distribution network planning and asset management applications. Future work can apply intelligent control techniques that consider the online communication among the placed ESSs. Optimal operation of ESSs considering RES uncertainty and comprehensive ESS sizing can also be investigated.

4.8 Chapter 4 appendices

The system data used for the IEEE 33 distribution network test system is presented in Table 4.6 [67].
### Table 4.6: Used data for 33-bus test system [67]

<table>
<thead>
<tr>
<th>Line Number</th>
<th>Sending Bus</th>
<th>Receiving Bus</th>
<th>Resistance (Ω)</th>
<th>Reactance (Ω)</th>
<th>Load at Receiving End Bus</th>
<th>Real Power (kW)</th>
<th>Reactive Power (kVar)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L01</td>
<td>B01 (Main SS)</td>
<td>B02</td>
<td>0.0922</td>
<td>0.0477</td>
<td></td>
<td>100</td>
<td>60</td>
</tr>
<tr>
<td>L02</td>
<td>B02</td>
<td>B03</td>
<td>0.4580</td>
<td>0.2151</td>
<td></td>
<td>90</td>
<td>40</td>
</tr>
<tr>
<td>L03</td>
<td>B03</td>
<td>B04</td>
<td>0.3660</td>
<td>0.1864</td>
<td></td>
<td>120</td>
<td>80</td>
</tr>
<tr>
<td>L04</td>
<td>B04</td>
<td>B05</td>
<td>0.3811</td>
<td>0.1941</td>
<td></td>
<td>60</td>
<td>30</td>
</tr>
<tr>
<td>L05</td>
<td>B05</td>
<td>B06</td>
<td>0.8190</td>
<td>0.7070</td>
<td></td>
<td>60</td>
<td>20</td>
</tr>
<tr>
<td>L06</td>
<td>B06</td>
<td>B07</td>
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***Tie Lines, Substation Voltage = 12.66 kV***
Chapter 4 references


Chapter 5

Optimal ESS Placement and Sizing Using PQ Injection Approach

This chapter presents a strategy for optimal allocation of distributed ESSs through \( P \) and \( Q \) injection by the ESSs to a distribution network. The investigation is carried out in a renewable-penetrated (wind and solar) medium voltage IEEE-33 bus distribution network for two different scenarios: (1) using a uniform ESS size and (2) using non-uniform ESS sizes. DIgSILENT PowerFactory is used for system modeling and testing, and simulation events are automated using Python scripting. A hybrid meta-heuristic optimization algorithm such as the fitness-scaled chaotic artificial bee colony (FSCABC) algorithm is applied to optimize parameters of the objective function. The artificial bee colony (ABC) algorithm is also applied to justify the results attained from the FSCABC algorithm. The obtained results suggest that the proposed PQ injection-based ESS placement strategy performs better than the \( P \) injection-based approach, which can significantly improve distribution network performance by minimizing voltage deviation, power losses, and line loading.
5. OPTIMAL ESS PLACEMENT AND SIZING USING PQ INJECTION APPROACH

5.1 Introduction

Energy storage systems (ESSs) are growingly being integrated in distribution networks to offer various advantages related to technical, economic, and environmental issues [1]. These encompass facilitating renewable energy source (RES) integration [2–4], power loss minimization [5], load levelling [6] and peak shaving [7], load shifting [8, 9], frequency regulation [10, 11], energy management [12], demand management [13], mitigation of voltage deviation [14, 15], power quality improvement [10, 16], congestion management [17], RES energy time-shifting [18] and distributed generation planning [19], operating reserves [10, 20], network expansion [21, 22], overall cost reduction [23, 24] and profit maximization [10, 25], greenhouse gas (GHG) reduction [26, 27], and network reliability [28, 29]. However, the benefits from the ESS placement cannot be achieved in cases of their misuse or misplacement in distribution networks [30].

Asset management in distribution networks is considered as a vital task by network service providers for ensuring reliable network operation. However, this can be an expensive task which might increase network cost, such as the cost due to network reinforcement for voltage and thermal stability. Consequently, electricity prices can be affected significantly. Therefore, providing a low cost solution to distribution network operators targeting a better asset management practice is the motivation of this work. Optimal allocation of ESSs, based on performance expectations and optimization approaches, is reported in several studies [10, 14, 16, 21, 23, 24, 28, 31–48].

A comprehensive review on ESS placement, sizing, and operation is presented in [1] for mitigating the issues of distribution networks. This study also presents the role of ESSs for power quality improvement. In [31], an optimal allocation of ESSs is performed in an IEEE-33 bus distribution network to minimize voltage deviation, line losses, and line loading. In that paper, the ESS sizing is accomplished through the application of a unity power factor (p.f.) approach on the dispatch of ESSs, where the ESSs only inject P to the network. Ref. [21] proposes an optimal placement of distributed community-based ESSs in distribution networks to achieve the benefits from energy loss reduction, energy arbitrage, peaking photovoltaic (PV) generation, emission reduction, network upgrade deferral, and Var support.
An optimal placement and sizing of ESSs, for improving voltage profile of a wind-penetrated distribution system and minimizing cost of the system, is accomplished in [32]. In [33], the planning and control of ESSs is performed in an RES-integrated distribution network to minimize operational and investment costs. In [34], the risk of energy transaction mechanisms for energy agents under a distribution company is mitigated through optimal ESS placement. In [35], ESS allocation is optimized for the risk mitigation of distribution companies while reducing operational costs and maximizing energy transaction profits. Total energy loss of a distribution network is minimized by optimal ESS placement and sizing in [36]. In [10], the net profit of distributed ESSs is maximized through the achievement of energy reserve and energy price arbitrage, distribution system congestion management, and a frequency regulation service through controlling active and reactive powers.

In [37], the ESS placement is accomplished for both distribution and transmission networks. The optimal ESS size on the distribution side is calculated to address peak load shaving and load curve smoothing. On transmission side, a sensitivity analysis is performed using a time domain power flow, complex-valued neural networks, and economic dispatch to place the ESSs. Ref [38] investigates the impact of ESS configuration and location on voltage profiles, power losses, and utilization of ESSs within a feeder of a low voltage (LV) distribution network. In [40], a multi-objective optimal ESS allocation and sizing problem is formulated to mitigate voltage deviations and improve supply quality, eliminate line congestions and load curtailment, and minimize electricity and distribution network costs.

An ESS allocation strategy is proposed in [41] to determine optimal ESS locations and sizes while improving reliability of distribution networks. In [39], an optimal ESS management strategy is proposed for an RES-penetrated distribution system to minimize energy losses of the network, GHG emissions, and overall power generation cost. In [23], an optimal ESS allocation problem applying network reconfiguration is formulated in an RES-penetrated distribution network to minimize costs of the system. In [42], optimal ESS placement and sizing are accomplished for maximizing distribution system benefits while managing loads, and minimizing total costs and net present value (NPV).

In [14], optimal allocation and operation are performed for distributed ESSs for improving load and generation hosting capability. As a result, peak demand and power
5. OPTIMAL ESS PLACEMENT AND SIZING USING PQ INJECTION APPROACH

loss are reduced achieving better voltage regulation. In [43], optimal ESS allocation in an LV distribution network is performed targeting the prevention of under- and over-voltages and minimization of total network costs (regarding ESS and network losses). In [44] and [45], the ESS allocation is performed for minimizing the problem of voltage fluctuations due to PV integrations in LV networks. Again in [16], the allocation of distributed ESSs is performed for minimizing both network losses and the energy cost in relation to congestion management and external grid, and for providing voltage support.

In [24], optimal ESS allocation is accomplished to maximize distribution network benefits through minimizing the costs of ESS installation, energy losses, maintenance, interruption, and system upgrade. In [46], a planning framework is developed for determining optimal location and sizes of distributed ESSs in wind-penetrated power systems to minimize costs in relation to wind curtailment and line congestion, and to maximize the normalized profit of ESS owners. In [28], optimal ESS placement is performed to minimize interruption and annual costs as well as improve reliability of distribution systems. In [47], a framework for optimal ESS allocation in a wind-penetrated power system is developed for maximizing the use of wind power and minimizing hourly social cost. In [48], the annual electricity cost is minimized through optimal ESS allocation in a wind-penetrated distribution network, where reliability enhancement and peak shaving are not considered.

In the above literature, various optimization and modeling techniques (single and hybrid) are employed for the optimal allocation of ESSs [10, 14, 16, 23, 24, 28, 31–36, 39–47]. In [31], the ABC algorithm is applied for optimal ESS allocation in distribution networks and the results are verified through the application of the particle swarm optimization (PSO) approach. A probabilistic load flow, a hybrid multi-objective PSO integrating a non-dominated sorting genetic algorithm (NSGA-II), and a five-point estimation method (5PEM) technique are used in [32]. Again, a fuzzy PSO (FPSO) is utilized in [35]. An optimal power flow (OPF) with mathematical modeling technique is applied in [36]. A multi-agent approach based on game theory is employed in [34]. Ref. [40] uses the AC-OPF and mixed-integer second order cone programming (MISOCOCP) approaches for optimal placement of ESSs. A mixed-integer linear programming (MILP) approach is applied for optimal ESS placement in [23] and [10], while [33] presents a network-aware technique for the planning and control of ESSs. In [39] and [46], the NSGA-II is used for
optimization, while [41] employs a mixed-integer nonlinear programming approach for problem formulation and the PSO for optimization. Ref. [44] applies a genetic algorithm (GA)-based technique combined with simulated annealing, while [45] applies a GA-based bi-level optimization strategy for solving optimal ESS placement problem. Again in [16], an alternating direction technique to multipliers is employed for the placement of distributed ESSs. In [43], clustering and sensitivity analysis and the multi-period OPF approaches are applied. The GA (integrated with linear-programming) and a sequential Monte Carlo simulation (MCS) are used in [24, 28], while these strategies along with MATLAB optimization toolbox are employed in [42]. A multi-objective optimization technique (cost-based) by MATLAB is used in [14]. In [47], a GA, a market-based probabilistic OPF, and an energy arbitrage model are utilized. However, the application of hybrid optimization algorithms is also recommended in [1, 49, 50] for obtaining good optimal solutions.

This research introduces a hybrid optimization technique, namely FSCABC algorithm [51, 52] for optimal placement of ESSs. Being simple and robust, the ABC algorithm has triple search capability to solve complex combinatorial and multi-dimensional optimization problems [31, 53–55]. The hybrid FSCABC technique improves the performance of ABC algorithm by eliminating the trapping problem in local optima [51, 52, 56]. In comparison with centralized placement, distributed ESS allocation provides greater flexibility and more opportunities in terms of problem mitigation in a large distribution network [31, 32, 47]. Although various issues of distribution networks are addressed in the aforementioned literature, very few studies [31] focus on voltage profile improvement, line loading minimization, and power loss reduction. Moreover, the investigations for optimal ESS placement are carried out in [31] injecting P only (Q=0) from the ESSs to the network. However, the performance can be improved further with P and Q injection by the ESSs. This research has addressed this need.

In this study, an optimal placement problem of distributed ESSs, in an IEEE-33 bus distribution network, is investigated and formulated. DIgSILENT PowerFactory is used for system modeling and analysis, and the FSCABC optimization technique is employed for optimization. Python programming language is utilized for controlling the models developed in PowerFactory and facilitate optimization. The key contributions of this chapter are outlined as follows:
5. OPTIMAL ESS PLACEMENT AND SIZING USING PQ INJECTION APPROACH

- The investigation for optimal allocation of ESSs is carried out focusing on voltage profile improvement, line loading reduction, power loss minimization (real and reactive), and ultimately cost minimization. The optimal ESS allocation related research such as [16, 32, 38, 43] have not widely considered these parameters together except [31]. Although similar investigation is carried out in [31], a unity p.f. approach is applied on the ESS dispatch (i.e. the ESSs only inject P to the network). In this study, however, the ESSs inject both the P and Q to the network for better performance improvement with variable p.f. on the dispatch of an ESS.

- The ESSs are placed in the networks by two different approaches: (1) using a uniform ESS size, and (2) using non-uniform ESS sizes. These sort of approaches have not been utilized by earlier studies such as [14, 16, 34, 35, 38, 40, 47, 48] except [31]. The results obtained by using these approaches are analyzed and compared with [31] which establishes the performance improvement. Although the FSCABC optimization technique is applied for these investigations, ABC algorithm is also utilized to verify the results attained from the FSCABC approach.

- The performance indices are estimated to monitor the performance improvement after optimal ESS placement in the network, which are not estimated by the related studies except [31].

5.2 Modeling of the ESS

The selection of utility-scale ESSs relies upon various performance factors, technical characteristics, and applications [1]. Similar to [31], the UltraBattery (also called advanced lead-acid battery) is selected in this research from the viewpoint of ESS cost. Although the UltraBattery is selected as the ESS technology, the proposed ESS model is taken into account as generic and can be utilized for other ESS technologies.

The ESS model is subjects to the following constraints:

- The ESS is fully charged if state of charge $SOC_{ESS}^x = 1$ and fully discharged if $SOC_{ESS}^x = 0$. 
5.3 Formulation of the problem

- The ESS should control the real power in both ways and the $SOC_{ESS}^x$ is subject to the following constraint [57]:

$$0.2 \leq SOC_{ESS}^x \leq 0.9 \quad (5.1)$$

- A priority for real and reactive powers (P and Q) is required to satisfy the rated apparent power $S_{APP} = \sqrt{P^2 + Q^2}$.

In addition, the ESS should satisfy boundary conditions from (5.2) to (5.7) in time $t$ (indexed 1, ..., $NT$) [31]. The charging and discharging powers are estimated through (5.2) and (5.3), respectively [31]. Restrictions on energy stored by the ESS and ESS charging power are applied by (5.4) and (5.5), respectively. Furthermore, the constraints for energy released from the ESS and power discharged by the ESS are defined by (5.6) and (5.7), respectively [31].

$$P_{ESS,C}^t = \max \left\{ P_{ESS-MIN}, \frac{(E_{ESS}^t - S_{ESS-MAX})}{\eta_C} \cdot \Delta t \right\} \quad (5.2)$$

$$P_{ESS,D}^t = \min \left\{ P_{ESS-MAX}, \frac{(E_{ESS}^t - S_{ESS-MIN})}{\eta_D} \right\} \quad (5.3)$$

Charging mode:

$$E_{ESS}^{t+1} = \min \left\{ (E_{ESS}^t - \Delta t P_{ESS,C}^t \eta_C), S_{ESS-MAX} \right\} \quad (5.4)$$

$$P_{ESS,C}^t \leq P_{ESS}^t \leq P_{ESS,D}^t \quad (5.5)$$

Discharging mode:

$$E_{ESS}^{t+1} = \max \left\{ (E_{ESS}^t - \Delta t \frac{P_{ESS,D}^t}{\eta_D}), S_{ESS-MIN} \right\} \quad (5.6)$$

$$P_{ESS,C}^t \leq P_{ESS}^t \leq P_{ESS,D}^t \quad (5.7)$$

5.3 Formulation of the problem

5.3.1 Objective function

The objective function of the proposed optimal ESS allocation problem is given in (5.8) and formulated using (5.9) to (5.16) [31]. This is a cost function which includes the
5. OPTIMAL ESS PLACEMENT AND SIZING USING PQ INJECTION APPROACH

costs in relation to network performance such as voltage deviation, line loading, and line losses as well as ESS units [31]. This function comprises the performance cost factors \((C_{VDev}^n, C_{LLd}^l, and C_{PLs}^l)\) as well as ESS cost factor \((C_{ESS}^{UTo})\) which are weighted equally with \(\beta_{VDev} = \beta_{LLd} = \beta_{PLs} = \beta_{ESS} = 1\).

\[
\beta(C_{Fi}) = \text{minimize} \left\{ \beta_{VDev} \cdot C_{VDev}^n + \beta_{LLd} \cdot C_{LLd}^l + \beta_{PLs} \cdot C_{PLs}^l + (\beta_{ESS} \cdot C_{ESS}^{UTo}) \right\}
\]

where,

\[
C_{VDev}^n = \left( \sum_{n=1}^{N} |V_{Target} - V^n_B(S^n_{ESSP}, S^n_{ESSQ}, \lambda^n_{ESS})| \right) \cdot \gamma_{VDev}
\]

\[
C_{LLd}^l = \left( \sum_{l=1}^{M} \% LLd^l_{ESS}(S^n_{ESSP}, S^n_{ESSQ}, \lambda^n_{ESS}) \right) \cdot \gamma_{LLd}
\]

\[
\% LLd^l_{ESS}(S^n_{ESSP}, S^n_{ESSQ}, \lambda^n_{ESS}) = \left( \frac{SL^l_{ESS}}{SL_{RATED}} \right) \times 100
\]

\[
C_{PLs}^l = X_{TLLoss} \cdot \gamma_{PLs}
\]

\[
X_{TLLoss} = \sqrt{\left\{ P_{LT}(S^n_{ESSP}, S^n_{ESSQ}, \lambda^n_{ESS}) \right\}^2 + \left\{ Q_{LT}(S^n_{ESSP}, S^n_{ESSQ}, \lambda^n_{ESS}) \right\}^2}
\]

\[
P_{LT}(S^n_{ESSP}, S^n_{ESSQ}, \lambda^n_{ESS}) = \sum_{l=1}^{M} P_L(i,j) = \sum_{l=1}^{M} \left( R_L(i,j) \cdot \frac{P_i^2 + Q_i^2}{\| V^n_B(S^n_{ESSP}, S^n_{ESSQ}, \lambda^n_{ESS}) \|^2} \right)
\]

\[
Q_{LT}(S^n_{ESSP}, S^n_{ESSQ}, \lambda^n_{ESS}) = \sum_{l=1}^{M} Q_L(i,j) = \sum_{l=1}^{M} \left( X_L(i,j) \cdot \frac{P_i^2 + Q_i^2}{\| V^n_B(S^n_{ESSP}, S^n_{ESSQ}, \lambda^n_{ESS}) \|^2} \right)
\]

The total ESS unit cost is estimated by (5.16) [31]:

\[
C_{ESS}^{UTo} = \sum_{n=1}^{K} S^n_{ESS} \cdot C_{UU}
\]

In the above-mentioned equations, \(\gamma_{VDev} = 0.142 \text{ p.u.}\) [14, 31], \(\gamma_{LLd} = 0.503 \text{ p.u.}\) [31, 58], \(\gamma_{PLs} = 0.265 /\text{kWh}\) [31, 58], and \(V_{Target} = 1 \text{ p.u.}\). Additionally, \(C_{UU} = 460 /\text{kWh}\) considering UltraBattery applications in relation to industrial and commercial energy management [31, 59].
5.3 Formulation of the problem

5.3.2 Constraints of the objective function

The objective function presented in (5.8) is subject to (5.17) to (5.27) including ESS modeling related equations (5.1) to (5.7) [31]:

\[ P_i^G + \sum_{j \in J^+} (P_{j \rightarrow i}^D) = P_i^C + \sum_{k \in J^-} (P_{i \rightarrow k}^D) \]  \hspace{1cm} (5.17)

\[ Q_i^G + \sum_{j \in J^+} (Q_{j \rightarrow i}^D) = Q_i^C + \sum_{k \in J^-} (Q_{i \rightarrow k}^D) \]  \hspace{1cm} (5.18)

\[ V_{MIN} < |V_B^n| < V_{MAX} \]  \hspace{1cm} (5.19)

\[ PF_{ESS-MIN} \leq PF_{ESS} \leq PF_{ESS-MAX} \]  \hspace{1cm} (5.20)

\[ SL_{l-t}^l < SL_{l MAX} \]  \hspace{1cm} (5.21)

\[ \lambda^n_{ESS} = \begin{cases} 0, & \text{if the ESS is active} \\ 1, & \text{otherwise} \end{cases} \]  \hspace{1cm} (5.22)

\[ S^n_{ESSP} = \begin{cases} \text{Assign}, & \text{if } \lambda^n_{ESS}=0 \\ 0, & \text{if } \lambda^n_{ESS}=1 \end{cases} \]  \hspace{1cm} (5.23)

\[ S^n_{ESSQ} = \begin{cases} \text{Assign}, & \text{if } \lambda^n_{ESS}=0 \\ 0, & \text{if } \lambda^n_{ESS}=1 \end{cases} \]  \hspace{1cm} (5.24)

\[ P_{ESS-MIN} < P_{ESS} < P_{ESS-MAX} \]  \hspace{1cm} (5.25)

\[ P^t_{ESS,C} \leq P^t_{ESS} \leq P^t_{ESS,D} \]  \hspace{1cm} (5.26)

\[ E_{ESS-MIN} < E_{ESS} < E_{ESS-MAX} \]  \hspace{1cm} (5.27)

where,

- Equations (5.17) and (5.18) signify the active and reactive power balance of a bus \( i \) [31].
- Equation (5.19) denotes the voltage constraint of each bus [31].
- Equation (5.20) ensures that the p.f. on the dispatch of an ESS within the range 0.95 to 1 [60].
5. OPTIMAL ESS PLACEMENT AND SIZING USING PQ INJECTION APPROACH

- Equation (5.21) guarantees that the line loading of line \( l \) must not surpass the maximum boundary \( SL_{l, max} \) to safeguard the thermal stability of cables. The \( SL_{l, max} \) is considered as 80% based on industry practices of planning as described in [31].

- Equations (5.22) to (5.24) denote the ESS allocation constraints.

- Equations (5.25) to (5.27) guarantee that the ESS power or energy must not surpass their maximum limits throughout charging and discharging phases. Additionally, (5.1) to (5.7) assure the operation of ESSs within the specified SOC limits [31].

5.4 FSCABC optimization and proposed approaches

5.4.1 FSCABC optimization approach

In this research, the FSCABC algorithm proposed in [51, 52] is applied for optimizing the grid-connected ESS placement problem. The ABC algorithm is proposed by Karaboga in 2005 [54, 61, 62], which is a bio-inspired swarm intelligence metaheuristic search technique. The possibility of being trapped in local optima while using ABC algorithm [51, 52, 56] can be solved by hybridization with two useful approaches: (1) the fitness scaling approach; and (2) the chaotic approach [51, 52].

With the first approach, the raw fitness values are scaled in a range suited to selection function which are used to select the next generations bees with a high probability of selection to bees. This basically converts the raw fitness results (which are returned by the fitness function) to values well-matched to selection function. The chaotic approach enriches the searching behavior of traditional ABC and assists to avoid the trapping possibility into local optimum [51]. Chaos theory is characterized by the well-known butterfly effect ascertained by Lorenz [63]. After searching by each bee of ABC colony, the chaotic search is conducted in the neighborhood of the present best solution which provides a better solution into the subsequent generation phase. With the above considerations, the FSABC is applied for optimizing the proposed ESS placement problem. The overall FSCABC optimization process is clarified by the flow chart as depicted in Fig. 5.1(a).
5.4 FSCABC optimization and proposed approaches

Among many fitness scaling methods such as linear, rank, power and top scaling, the power and rank scaling are hybridized to remove their individual limitations. For instance, power scaling can find a solution promptly while having instability problem and rank scaling performs better in terms of stability. Hence, a new power-rank scaling technique, combining both power and rank strategies, is proposed as follows:

\[ fit_{SCALE}^i = \frac{r^q_{a-i}}{\sum_{i=1}^{FS} r^q_{a-i}} \]  \hspace{1cm} (5.28)
where, \( r_{a-i} \) = the rank of \( i \)th bee, \( FS \) = the number of food sources, and \( q \) = the exponential value for power computation.

According to the chaos theory, minute changes in initial conditions cause widely diverging outcomes, providing long-term behavioural prediction impossible in general [52]. The chaotic search is defined by the well-known logistic function as given in (5.29).

\[
x_i^{n+1} = \mu^{bif} x_i^n (1 - x_i^n), \quad i = 1, 2, ..., FS
\]  

(5.29)

where, \( x_i^n \) = the \( i \)th chaotic variable, \( n \) = the iteration number, and \( \mu^{bif} \) = the bifurcation parameter of the system with \( \mu^{bif} \in [0, 4] \). The chaotic behaviour is exhibited with \( \mu^{bif} = 4 \), \( x_0 \in (0, 1) \), and \( x_0 \notin \{0.25, 0.5, 0.75\} \).

In the initialization phase, the colony size (\( CS \)) of solutions \( x_{ij} (i = 1, 2, ..., FS; j = 1, 2, ..., PD) \) (\( PD \) = problem dimension) is determined with the number of employed bees (\( N_{EmB} \)) and the number of onlooker bees (\( N_{OnB} \)), while satisfying \( CS = N_{EmB} + N_{OnB} \). The population is initialized with \( j = 0 \) as represented in (5.30).

\[
x_{i0} = LB + \psi_{ij}^{rand} (UB - LB), \quad i = 1, 2, ..., FS
\]  

(5.30)

where, \( LB \) = the lower boundary, \( UB \) = the upper boundary, and \( \psi_{ij}^{rand} \) = a random number within the range \([0, 1]\). By applying the following equation, each employed bee travels from one old position \( x_{ij} \) to a new candidate position \( v_{ij} \):

\[
v_{ij} = x_{ij} + \Phi_{ij}^{rand} (x_{ij} - x_{kj})
\]  

(5.31)

In (5.31), \( k \in 1, 2, ..., FS \) and \( j \in 1, 2, ..., PD \) are randomly nominated and \( k \) should be different from \( i \), where, \( \Phi_{ij}^{rand} \) = uniform random number within the range \([-1, 1]\). If the new position value \( v_{ij} \) is better than \( x_{ij} \), then \( x_{ij} \) is updated with \( v_{ij} \), otherwise \( x_{ij} \) remains unaltered. The probability of a food source (\( p_i \)) and the fitness scores of food sources of employed bees (\( fit^{fs} \)) are estimated by (5.32) and (5.33), respectively, where, \( f(x_i)_{obj} \) signifies the values of a objective function to be optimized.

\[
p_i = \frac{fit_i^{fs}}{\sum_{j=1}^{FS} fit_j^{fs}}
\]  

(5.32)
5.4 FSCABC optimization and proposed approaches

\[ f_{i}^{fs} = \begin{cases} \frac{1}{1 + f(x_i)^{obj}}, & f(x_i)^{obj} \geq 0 \\ 1 + |f(x_i)^{obj}|, & f(x_i)^{obj} < 0 \end{cases} \] (5.33)

Depending on the \( p_i \) value, the onlooker bee chooses a food source by applying a roulette wheel selection approach and then this new location is determined by (5.34), where \( \omega_i^{EB} \) = weight coefficient in relation to employed bee information.

\[ u_{ij} = x_{ij} + \omega_i^{EB} \Phi_{ij}^{rand} (x_{ij} - x_{kj}) \] (5.34)

As the parameter \( \Phi \) is the key factor for convergence in ABC [51], the chaotic sequence of this parameter is defined by (5.35) and applied into (5.31) & (5.34).

\[ \Phi_{ij}^{CHAOS} = 2 \times \left[ 4 \Phi_{ij}^{rand} \left( 1 - \Phi_{ij}^{rand} \right) \right] - 1 \] (5.35)

The abandoned solutions are improved in the scout bee phase and replaced by a new solution \( x_{ij}^{CHAOS} \) as given in (5.36).

\[ x_{ij}^{CHAOS} = \min (x_{ij}) + \varphi_{ij}^{rand} \left[ \max (x_{ij}) - \min (x_{ij}) \right] \] (5.36)

where, \( \max(x_{ij}) = \max \{ x_{1j}, x_{2j}, ..., x_{Nj} \} \), \( \min(x_{ij}) = \min \{ x_{1j}, x_{2j}, ..., x_{Nj} \} \), and \( \varphi_{ij}^{rand} \) = a random number within the range \([-1, 1]\). Similar to parameter \( \Phi \), the chaotic sequence of \( \varphi_{ij}^{rand} \) is defined by (5.37) and applied into (5.36).

\[ \varphi_{ij}^{CHAOS} = 4 \varphi_{ij}^{rand} \left( 1 - \varphi_{ij}^{rand} \right) \] (5.37)

5.4.2 Proposed approach

Figure 5.1(b) represents the proposed methodology for solving the optimal ESS allocation problem. The FSCABC parameters are initialized after entering all the necessary component data in a distribution network. The parameters and variables of FSCABC optimization process are summarized in Table 5.1. For feeder load scaling, the \( P_{T-F} \) & \( Q_{T-F} \) are entered to the feeder and a voltage dependency of loads is created. The time-variant characteristics of [31] are applied for characterizing the loads, wind, and solar DGs. Subsequently, the problem is formulated to minimize the sum of \( C_{VDev}^n \)
5. OPTIMAL ESS PLACEMENT AND SIZING USING PQ INJECTION APPROACH

$C_{LLd}^l$, $C_{PLs}^l$, and $C_{UTo}^l$. The investigations are carried out in two stages: (1) investigation category I—using a uniform ESS size; and (2) investigation category II—using non-uniform ESS sizes.

Table 5.1: Parameters and variables of FSCABC optimization approach

<table>
<thead>
<tr>
<th>Type</th>
<th>Parameters/variables</th>
<th>Description/settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input parameters</td>
<td>$V_{HATED}, R_{L(i,j)}, X_{L(i,j)}, P, Q, P_{T-F}, Q_{T-F}, S_{WIND}, S_{PV-MAX}$, $S_{PV-OP}$, and $S_{ESS-MAX}$</td>
<td>Essential for the distribution network model.</td>
</tr>
<tr>
<td>Output parameters</td>
<td>$C_{UDev}, C_{LLd}^l, C_{PLs}^l$, and $C_{UTo}^l$</td>
<td>Essential for the objective function.</td>
</tr>
<tr>
<td>Decision variables</td>
<td>$S_{ESSP}$, $S_{ESSQ}$, and $\lambda_{ESS}$</td>
<td>This variable represents the amount of P injection from the ESSs in the network.</td>
</tr>
<tr>
<td>Decision variables</td>
<td>$\mu_{bif}$, $\psi_{rand}^{ij}$, $\Phi_{rand}^{ij}$, $\phi_{rand}^{ij}$, and $x_0^i$</td>
<td>Settings: $\mu_{bif} \in [0, 4]$, $\psi_{rand}^{ij} \in [0, 1]$, $\Phi_{rand}^{ij} \in [-1, 1]$, $\phi_{rand}^{ij} \in [-1, 1]$, $x_0^i \in (0, 1)$, and $x_0^i \notin {0.25, 0.5, 0.75}$.</td>
</tr>
<tr>
<td>FSCABC bounds</td>
<td>$PD$, $CS$, $FS$, $L_{TRIAL}$, and $I_{MAX}$</td>
<td>Settings: $PD = 3$, $CS = 100$, $FS = CS/2 = $population size, $L_{TRIAL} = 60$, and $I_{MAX} = 1000$.</td>
</tr>
</tbody>
</table>

The ESS locations are determined through the decision variable $\lambda_{ESS}$ (can be 0 or 1, while 0 signifies the ESS is active and 1 means inactive). The size of an ESS (MVA) in the network is obtained from the decision variables $S_{ESSP}$ (MW) and $S_{ESSQ}$ (MVar). The $S_{ESSP}$, $S_{ESSQ}$, and $\lambda_{ESS}$ are generated randomly within the selected ranges and applied to the system. The $S_{ESSP}$ and $S_{ESSQ}$ are injected such that the maximum number of ESSs having lower capacity (in the ranges $P = 0.1$ MW to 2 MW, $Q = 0.1$ MVar to 1 MVar for investigation category I and $P = 0.1$ MW to 2.5 MW, $Q = 0.1$ MVar to 1 MVar for investigation category II) can be dispersed in the network. During investigation category II, the $S_{ESSQ}$ is kept uniform for all ESSs on the network, while the $S_{ESSP}$ is assigned non-uniformly to the ESSs. The initial values are nominated randomly according to the selected ranges of P and Q, and ESS sizes to be tested on.
the network. The overall nomination of ESS sizes is subject to $LB_1$, $UB_1$, $LB_2$, $UB_2$, $LB_3$, $UB_3$, AC and DC bus sizes, transformer size, string size of ESSs, and inverter specifications. Finally, the FSCABC optimization process determines the optimal values of $S^n_{ESSP}$, $S^n_{ESSQ}$, and $\lambda^n_{ESS}$ by fulfilling the objective function constraints.

In this research, a variable p.f. (within the range 0.95 to 1) approach for sizing is applied to the dispatch of ESSs. The intention of the approach is that the ESSs will inject both P and Q rather than injecting P only (the unity p.f. case). This approach improves the performance of the network through more reactive power compensation. Hence, the ESS locations and size are found utilizing the multi-functionality of ESSs in supplying the MW and MVar required to assist the voltage controllers on the network and minimize line loading and losses.

5.5 Testing, factor assignment, and performance indices

This section explores the distribution network used for testing of the proposed approach, the assignment of essential factors, and necessary indices to evaluate the improvements of system performance. The details of the factor assignment and performance measurement can be found in [31].

5.5.1 Test network

The proposed approach is tested in a distribution system whose single line diagram is illustrated in Fig. 5.2. This is an IEEE-33 bus distribution network (radial) whose detailed model can be found in [31]. The buses are denoted by numbers (1 to 33) and the lines are indicated by the letter ‘L’. Bus 1 is the feeder and lines L33 to L37 are the tie lines of the network [31]. The ESS model (described in Section 5.2) is allocated distributively throughout the network. A high RES penetration scenario is built by incorporating two wind DGs and seven solar DGs. The loads, wind DGs, and solar DGs are modeled using built-in templates of PowerFactory and applying the data found in [31]. The wind DGs, namely WDG1 and WDG2, are allocated on bus 18 and bus 24, respectively, while the solar DGs- PV1, PV2, PV3, PV4, PV5, PV6, and PV7 are located on bus 5, bus 21, bus 31, bus 8, bus 12, bus 28, and bus 33, respectively. The overall
system model information is: base MVA = 10 MVA; substation voltage = 12.66 kV; size of WDG1 & WDG2 = 1 MW; size of PV1, PV2, & PV3 = 400 kVA; size of PV4, PV5, PV6, & PV7 = 500 kVA; $P_{T-F} = 3.715$ MW; $Q_{T-F} = 2.3$ MVar; and $S_{PV-OP} = 85\%$ of $S_{PV-MAX}$ [31].

**Figure 5.2:** Single-line diagram of the distribution network model.

### 5.5.2 Assignment of scaling factors and voltage dependency

The system loads follow the IEEE-RTS model and the loads of the feeder are scaled by following the steps described in [31]. The total real and reactive powers are computed using a scale ($\Psi_{SCALE}$) and considering the voltage dependency of loads as presented in (5.38) and (5.39), respectively [31].

\[
P = \Psi_{SCALE} \cdot P_0 \left[ aP \cdot \left( \frac{V_B}{V_{REF}} \right)^{eAP} + bP \cdot \left( \frac{V_B}{V_{REF}} \right)^{eBP} + (1 - aP - bP) \cdot \left( \frac{V_B}{V_{REF}} \right)^{eCP} \right]
\] (5.38)
5.5 Testing, factor assignment, and performance indices

\[ Q = \Psi_{SCALE} \cdot Q_0 \left[ aQ \cdot \left( \frac{V_B^n}{V_{REF}} \right)^{e_{aQ}} + bQ \cdot \left( \frac{V_B^n}{V_{REF}} \right)^{e_{bQ}} + (1 - aQ - bQ) \cdot \left( \frac{V_B^n}{V_{REF}} \right)^{e_{cQ}} \right] \]

(5.39)

where, \((1 - aP - bP) = cP\) and \((1 - aQ - bQ) = cQ\).

The assigned load coefficients are \(aP = aQ = 0.4\), \(bP = bQ = 0.3\), and \(cP = cQ = 0.3\), and the set exponents are \(e_{aP} = e_{aQ} = 0\), \(e_{bP} = e_{bQ} = 1\), and \(e_{cP} = e_{cQ} = 2\) [31]. The scaling of RES generation (wind and solar DGs) outputs is accomplished as per the characteristics provided in [31].

5.5.3 Performance indices of the system

5.5.3.1 Indices for voltage deviation and profile improvement

Considering ±5% deviation limit, the \(V_{MAX}\), \(V_{MIN}\), and voltage deviation for \(n\)th bus are calculated. The voltage deviation index \((VDevI)\) is expressed as a percentage and defined by (5.40) [31].

\[ \% VDevI = \sum_{n=1}^{N} \left( \frac{|V_{RATED} - V_B^n|}{V_{RATED}} \right) \times 100 \]  

(5.40)

The voltage profile of \(n\)th bus, overall voltage profile, and the voltage profile improvement index of the system are defined by (5.41), (5.42), and (5.43), respectively [31].

\[ VProf^n = V_B^n S_{Ld}^n \Pi^n \]  

(5.41)

\[ VProf = \sum_{n=1}^{N} VProf^n \]  

(5.42)

\[ VPII = \frac{VProf_{w-ESS}}{VProf_{wo-ESS}} \]  

(5.43)

where,

\[ \sum_{i=1}^{N} \Pi^n = 1 \]  

(5.44)
5. OPTIMAL ESS PLACEMENT AND SIZING USING PQ INJECTION APPROACH

5.5.3.2 Index for line loading

The index for line loading ($LLdI$) represents the measurement of total loading or demand levels of lines, which is defined by (5.45) [31]. In this study, the percent line loading of $l$th line, for base case and after ESS placement, is formulated by (5.46) and (5.11), respectively [31].

\[
LLdI = \frac{\% LLdT_{w-ESS}}{\% LLdT_{wo-ESS}} = \frac{\sum_{l=1}^{M} \% LLd_{l}^{ESS}}{\sum_{l=1}^{M} \% LLd_{l}^{BASE}} \quad (5.45)
\]

\[
% \; LLd_{BASE} = \left( \frac{SL_{BASE}^{l}}{S_{RATED}^{l}} \right) \times 100 \quad (5.46)
\]

5.5.3.3 Indices for power loss reduction

The indices for the reduction of active, reactive, and total power losses ($PLsRI_{P}$, $PLsRI_{Q}$, and $PLsRI_{T}$) are demarcated by (5.47), (5.48), and (5.49), respectively [31].

\[
PLsRI_{P} = \frac{\sum_{l=1}^{M} P_{l}^{ESS}}{\sum_{l=1}^{M} P_{l}^{BASE}} \quad (5.47)
\]

\[
PLsRI_{Q} = \frac{\sum_{l=1}^{M} Q_{l}^{ESS}}{\sum_{l=1}^{M} Q_{l}^{BASE}} \quad (5.48)
\]

\[
PLsRI_{T} = \frac{\sum_{l=1}^{M} \sqrt{(P_{l}^{ESS})^2 + (Q_{l}^{ESS})^2}}{\sum_{l=1}^{M} \sqrt{(P_{l}^{BASE})^2 + (Q_{l}^{BASE})^2}} \quad (5.49)
\]

5.6 Results and discussion

This section explores the impact of optimal ESS placement through the PQ injection (on the dispatch of ESSs) to the distribution system. The performance of the system is analyzed in three different case studies: Case 1—without ESS placement (base case), Case 2—ESS placement for a uniform ESS size, and Case 3—ESS placement for non-uniform ESS sizes. Optimal ESS allocation is performed by minimizing the objective function parameters for the same network scenario of [31]. As the ESSs inject P (MW)
and Q (MVar) to the network, the p.f. is variable which is limited by $PF_{MIN} = 0.95$ during optimization. The results of the system are summarized in Table 5.2. The investigation is conducted for a time period of 24 hours and the maximum value of parameters $\%VDevi$, $\%LldT$, $P_{Tot}$, and $Q_{Tot}$ for that period is calculated. This section also presents a result comparison between two approaches— the proposed PQ injection approach and the P injection approach of [31]— and reports the performance improvement. The system results using the P injection approach (achieved by [31]) are presented in Table 5.3, which are categorized as Case 4 and Case 5 for investigation category I and investigation category II, respectively. Similar to [31], the ESS power rating (MVA) is assumed constant over one hour. In addition, the results obtained from the FSCABC algorithm are compared with the ABC approach and presented in this section.

### Table 5.2: Obtained results from the proposed PQ injection approach

<table>
<thead>
<tr>
<th>P (MW), Q (MVar), and locations of ESSs</th>
<th>$%VDevi$</th>
<th>$%LldT$</th>
<th>$P_{Tot}$ (MW)</th>
<th>$Q_{Tot}$ (MVar)</th>
<th>Total ESS Size (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Case 1—Without placement of ESSs (base case)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No ESSs</td>
<td>89.73</td>
<td>269.81</td>
<td>0.11</td>
<td>0.09</td>
<td>-</td>
</tr>
<tr>
<td><strong>Case 2—Distributed ESS placement using a uniform ESS size</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESS9, ESS7, ESS9, ESS14, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs $P = 0.971$ $Q = 0.291$</td>
<td>67.339</td>
<td>221.849</td>
<td>0.0840</td>
<td>0.0607</td>
<td>8.109</td>
</tr>
<tr>
<td><strong>Case 3—Distributed ESS placement using non-uniform ESS sizes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESS7–P=1.191 Q=0.12; ESS10–P=0.715 Q=0.12; ESS14–P=0.798 Q=0.12; ESS16–P=0.368 Q=0.12; ESS17–P=0.368 Q=0.12; ESS22–P=0.368 Q=0.12; ESS25–P=2.5 Q=0.12; ESS31–P=0.368 Q=0.12; ESS32–P=0.693 Q=0.12</td>
<td>66.704</td>
<td>204.375</td>
<td>0.0738</td>
<td>0.0521</td>
<td>10.666</td>
</tr>
</tbody>
</table>

### Table 5.3: System results with the P injection approach obtained by [31]

<table>
<thead>
<tr>
<th>P (MW) and locations of ESSs</th>
<th>$%VDevi$</th>
<th>$%LldT$</th>
<th>$P_{Tot}$ (MW)</th>
<th>$Q_{Tot}$ (MVar)</th>
<th>Total ESS Size (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Case 4—Distributed ESS placement using a uniform ESS size</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESS9, ESS14, ESS25, ESS29, ESS30, ESS31, ESS32, for all ESSs $P=0.724$ $Q=0$</td>
<td>75.753</td>
<td>241.128</td>
<td>0.0905</td>
<td>0.0683</td>
<td>5.793</td>
</tr>
<tr>
<td><strong>Case 5—Distributed ESS placement using non-uniform ESS sizes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESS8–P=0.335; ESS10–P=0.378; ESS13–P=0.383; ESS16–P=0.823; ESS17–P=0.1; ESS20–P=0.128; ESS22–P=0.1; ESS25–P=2; ESS30–P=1.442; ESS31–P=0.725; ESS32–P=0.781; for all ESSs $Q=0$</td>
<td>72.162</td>
<td>240.039</td>
<td>0.0894</td>
<td>0.0666</td>
<td>7.195</td>
</tr>
</tbody>
</table>
5. OPTIMAL ESS PLACEMENT AND SIZING USING PQ INJECTION APPROACH

5.6.1 Case 1- base case without ESS placement

The reference values of the result parameters such as %\(V_{DevI}\), %\(LLdT\), \(P_{Tot}\), and \(Q_{Tot}\) for base case analysis is presented in Table 5.2. These base values are targeted to minimize through the proposed PQ injection approach of ESSs. Although the \(V_{Bi}\) is limited by \(V_{MAX}\) and \(V_{MIN}\), the voltage profile can be improved further. Similarly, the line loading and losses can be minimized through the proposed PQ injection approach.

5.6.2 Case 2- ESS placement using a uniform ESS size

The optimal ESS allocation results for uniform \(S_{ESSP}^n\) and \(S_{ESSQ}^n\) values (using the PQ injection approach) are presented in Table 5.2. The \(S_{ESSP}^n\), \(S_{ESSQ}^n\), and \(\lambda_{ESS}^n\) can be identified in Table 5.2 by the ESS MW (P), ESS MVar (Q), and ESS number, respectively: e.g., for ESS9, P=0.971 and Q=0.291 denote that an ESS of 0.971 MW and 0.291 MVar (total size of 1.014 MVA) is connected to bus 9. Eight ESSs of a uniform size (1.014 MVA) are placed on buses 7, 9, 14, 25, 29, 30, 31, and 32. All the parameters in Case 2 such as %\(V_{DevI}\), %\(LLdT\), \(P_{Tot}\), and \(Q_{Tot}\) are minimized compared to Case 1. A noticeable point is that all Case 2 parameters are also minimized compared to Case 4 (tabulated in Table 5.3). For instance, the values of %\(V_{DevI}\), %\(LLdT\), \(P_{Tot}\), and \(Q_{Tot}\) are 75.753%, 241.128%, 0.0905 MW, and 0.0683 MVar, respectively, while using the P injection approach [31]. In contrast, when using the PQ injection approach, these values are further reduced such as %\(V_{DevI}=67.339\%\), %\(LLdT=221.849\%\), \(P_{Tot}=0.0840\) MW, and \(Q_{Tot}=0.0607\) MVar. However, the total ESS size required in Case 2 to improve the performance is 8.109 MWh which is higher than the total ESS size of Case 4 (5.793 MWh). Hence, there is an increase of distribution system investment cost during Case 2 compared to Case 4, while improving the performance better than the Case 4.

5.6.3 Case 3- ESS placement using non-uniform ESS sizes

After analyzing the impact of optimal ESS placement using non-uniform ESS sizes using the PQ injection approach, the results are summarized in Table 5.2 as Case 3. In this case study, the \(S_{ESSP}^n\) is assigned non-uniformly to all ESSs and the \(S_{ESSQ}^n\) is allotted uniformly to all ESSs. The \(S_{ESSP}^n\), \(S_{ESSQ}^n\), and \(\lambda_{ESS}^n\) can be identified in Table
5.6 Results and discussion

5.2 by the ESS MW (P), ESS MVar (Q), and ESS number, respectively: e.g., ESS7-P = 1.191 Q=0.12 represents that an ESS of 1.191 MW and 0.12 MVar (total size of 1.033 MVA) is placed to bus 7. Eleven ESSs of non-uniform ESS sizes (as given in Table 5.2) are placed on buses 7, 10, 14, 16, 17, 22, 25, 29, 30, 31, and 32. It is apparent that all the parameters (%\(V_{DevI}\), %\(LL_{dT}\), \(P_{Tot}\), and \(Q_{Tot}\)) are further minimized compared to Case 2. It is also obvious that all Case 3 parameters are minimized compared to Case 5 (given in Table 5.3). For example, when using the P injection approach, the values of %\(V_{DevI}\), %\(LL_{dT}\), \(P_{Tot}\), and \(Q_{Tot}\) are 72.162%, 240.039%, 0.0894 MW, and 0.0666 MVar, respectively [31]. On the contrary, these values are further reduced while using the PQ injection approach such as %\(V_{DevI}\)=66.704%, %\(LL_{dT}\)=204.375%, \(P_{Tot}\)=0.0738 MW, and \(Q_{Tot}\)=0.0521 MVar. However, for Case 3, the required total ESS size is 10.666 MWh, which signifies an increment in distribution system investment cost over Case 2 (7.432 MWh) and Case 5 (7.195 MWh). This is mainly due to the fact that non-uniform ESS sizing approach (Case 3) is more adjustable in relation to overcoming network operational constraints compared to uniform ESS sizing method (Case 2) and can achieve more optimal performance across the whole network.

5.6.4 Overall result analysis and comparison using the PQ injection approach

5.6.4.1 Comparison in relation to voltage profiles

The voltage profiles using the PQ injection approach for Case 1, Case 2, and Case 3 are depicted in Fig. 5.3. The feeder voltage profiles for Case 2 and Case 3 (p.u. voltage vs km) are illustrated in Fig. 5.4 and Fig. 5.5, respectively. Various sections of feeder voltage profiles (in terms of feeder length) are indicated with different colors, where all the lines of the feeder have the same length (1km). Although both Case 2 and Case 3 have similar voltage profiles, Case 3 has improvements in the voltage profile at some buses as illustrated in Fig. 5.3. For instance, according to Fig. 5.3, Fig. 5.4, and Fig. 5.5, Case 3 has improved the bus voltage at bus 24 (Case 3=0.972 p.u., Case 2=0.975 p.u.) and bus 25 (Case 3=0.971 p.u., Case 2=0.976 p.u.) compared to Case 2. Similarly, the voltages are improved for Case 3 at buses 10, 22, 23, and 26 to 30 compared to Case 2. However, Case 2 has improved bus voltage characteristics at buses 7 to 9, 13 to 15, and 31 to 33 compared to Case 3. Figure 5.4 and Fig. 5.5 shows that the voltage drop in
5. OPTIMAL ESS PLACEMENT AND SIZING USING PQ INJECTION APPROACH

Figure 5.3: Voltage profiles for various cases using the PQ injection approach.

The feeder section L02-L22-L23-L24-L37-L29-L30 and L16-L17 is higher for Case 2, while Case 3 has higher voltage drops in sections L02-L22-L23-L24 and L08-L29-L30-L31-L32. The highest voltage drop for Case 2 and Case 3 is observed at bus 30 (0.974 p.u.) and bus 24 (0.974 p.u.), respectively. For both Case 2 and Case 3, lower voltage drops occur at buses 2 and 19. From the illustrations, it is evident that both Case 2 and Case 3 have good voltage profiles, where Case 3 (%\(V_{DevI}\)=66.704) provides a slightly better voltage profile than Case 2 (%\(V_{DevI}\)=67.339).

5.6.4.2 Comparison in relation to line loading

Figure 5.6 compares the percent line loadings of Case 1, Case 2, and Case 3, which implies that the loading of each line for all cases is below the maximum boundary 80%. It can be noted that L1 has a maximum loading of 40.801% for all cases, while L2 has about 28% loading for Case 1, 27.763% for Case 2, and 26.857% for Case 3. All other lines for Case 2 and Case 3 are lightly loaded (e.g., below 15%). From the viewpoint of line to line loading variation, the line loadings of Case 2 are higher at lines L2, L5-L6, L8-L9, L11, L13-L14, L17, L21-L23, L25-L26, L28-L31, L34-L35, and L37 compared to Case 3. In contrast, Case 3 provides higher loading values at lines L3, L7, L10, L15-L16, L18,
5.6 Results and discussion

Figure 5.4: The feeder voltage profile for case 2 using the PQ injection approach.

Figure 5.5: The feeder voltage profile for case 3 using the PQ injection approach.
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L24, L27, L22-L29, L32-L33, and L36 than Case 2. Overall, Case 3 (%LLdT=204.375) provides better line loadings than Case 2 (%LLdT=221.849). It is apparent from the line loading characteristics of Case 2 and Case 3 that the feeder has sufficient spare capacity to get back from the unexpected situation during outage.

5.6.4.3 Comparison in relation to line losses

Figure 5.7 compares the active, reactive, and total power losses of various lines for Case 2 and Case 3 over Case 1. According to Fig. 5.7(a), L2 has the highest active power loss of 0.0263 MW and 0.0246 MW for Case 2 and Case 3, respectively. Case 2 has a higher active power loss at lines L2, L4-L5, L7-L9,L13-L14, L17, L21-L23, L25-L26, L28, and L30, while a higher active power loss value is observed at lines L3, L7, L12, L15-L16, L19, L24, and L27 for Case 3. As referred to in Fig. 5.7(b), again L2 has the highest reactive power loss of 0.0134 MVar and 0.0125 MVar for Case 2 and Case 3, respectively. Besides, the reactive power loss and total line loss profiles for Case 2 and Case 3 at various lines is almost similar to the real power loss characteristics of Fig. 5.7(a) except the tie lines. Both Case 2 and Case 3 have reactive power losses in tie lines as depicted in Fig. 5.7(b). Overall, the losses are little bit higher for Case 2 (e.g., $P_{Tot}=0.0840$, and $Q_{Tot}=0.0607$) compared to Case 3 (e.g., $P_{Tot}=0.0738$, and $Q_{Tot}=0.0521$).
Figure 5.7: Comparison of losses for various cases using the PQ injection approach (a) active power loss, (b) reactive power loss, and (c) total line loss.
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5.6.4.4 Statistical analysis of FSCABC approach with ABC algorithm

The ABC algorithm is employed for ESS allocation in [31]. The overall ABC algorithm is demonstrated in Chapter 4, Section 4.4.1. The same ABC approach is utilized to verify the results found from the proposed FSCABC technique using the same settings of $PD$, $CS$, $FS$, $L_{TRIAL}$, and $It_{MAX}$ as listed in Table 5.1. Both the FSCABC and the ABC optimization are executed 30 times and the best, worst, and mean objective function values for investigation category I and investigation category II are compared in Table 5.4. In addition, the standard deviations for FSCABC and ABC algorithms ($\sigma_{FSCABC}$ and $\sigma_{ABC}$) of objective function values are calculated. The lesser value of standard deviation implies smaller deviation among solutions of 30 optimization runs. Table 5.4 suggests that the solutions obtained from both algorithms (in relation to objective function costs) are very close to each other. It is also evident that more optimal solutions are achieved from the FSCABC approach for both investigation categories. Therefore, it is apparent from the statistical analysis (presented in Table 5.4) that the proposed FSCABC technique is successful in attaining required optimal solutions of the problem for both investigation categories.

![Figure 5.8: Convergence of FSCABC and ABC algorithms.](image)

The computer configuration used for simulation is: Intel(R) Xeon 3.5 GHz processor, 64-bit windows 10, and 16 GB RAM. Figure 5.8 illustrates the convergence test char-
### Table 5.4: Optimization results of FSCABC and ABC for 30 runs

<table>
<thead>
<tr>
<th>Optimization statistics</th>
<th>ESS real &amp; reactive powers and locations</th>
<th>%VDevI</th>
<th>%LLdT</th>
<th>$P_{Tot}$ (MW)</th>
<th>$Q_{Tot}$ (MVar)</th>
<th>Total ESS size (MWh)</th>
<th>Objective function value ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FSCABC best</td>
<td>ESS7, ESS9, ESS14, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs P = 0.971 Q = 0.291</td>
<td>67.330</td>
<td>221.849</td>
<td>0.0840</td>
<td>0.0607</td>
<td>8.109</td>
<td>3730325.398</td>
</tr>
<tr>
<td>FSCABC worst</td>
<td>ESS7, ESS9, ESS13, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs P = 0.973 Q = 0.311</td>
<td>67.188</td>
<td>224.930</td>
<td>0.0846</td>
<td>0.0622</td>
<td>8.172</td>
<td>3759149.027</td>
</tr>
<tr>
<td>FSCABC mean</td>
<td>ESS7, ESS9, ESS13, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs P = 0.967 Q = 0.316</td>
<td>67.194</td>
<td>224.727</td>
<td>0.0846</td>
<td>0.0621</td>
<td>8.139</td>
<td>3743969.01</td>
</tr>
<tr>
<td>ABC best</td>
<td>ESS7, ESS9, ESS13, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs P = 0.965 Q = 0.316</td>
<td>67.228</td>
<td>224.699</td>
<td>0.0846</td>
<td>0.0621</td>
<td>8.123</td>
<td>3730609.01</td>
</tr>
<tr>
<td>ABC worst</td>
<td>ESS7, ESS9, ESS13, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs P = 0.974 Q = 0.319</td>
<td>67.020</td>
<td>224.748</td>
<td>0.0845</td>
<td>0.0622</td>
<td>8.199</td>
<td>3771569.004</td>
</tr>
<tr>
<td>ABC mean</td>
<td>ESS7, ESS9, ESS13, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs P = 0.969 Q = 0.318</td>
<td>67.123</td>
<td>224.702</td>
<td>0.0845</td>
<td>0.0621</td>
<td>8.159</td>
<td>3753168.989</td>
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<tr>
<td>$\sigma$ FSCABC</td>
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<td></td>
<td>104344.29</td>
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<td>$\sigma$ ABC</td>
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<td></td>
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<td>13313.388</td>
</tr>
</tbody>
</table>
## OPTIMAL ESS PLACEMENT AND SIZING USING PQ INJECTION APPROACH

Table 5.4 continues

<table>
<thead>
<tr>
<th>Objective function</th>
<th>ESS real &amp; reactive powers and locations</th>
<th>Optimization statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distributed ESS placement using non-uniform ESS sizes</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### ABC

**Best**

| ESS7-P=1.191 Q=0.12; ESS10-P=0.715 Q=0.12; ESS14-P=0.798 Q=0.12; ESS16-P=0.368 Q=0.12; ESS17-P=0.368 Q=0.12; ESS22-P=0.368 Q=0.12; ESS25-P=2.5 Q=0.12; ESS29-P=0.715 Q=0.12; ESS30-P=2.5 Q=0.12; ESS31-P=0.368 Q=0.12; ESS32-P=0.693 Q=0.12 | 66.704 | 204.375 | 0.0738 | 0.0521 | 10.666 | 4906385.04 |

**Worst**

| ESS7-P=1.256 Q=0.12; ESS10-P=0.689 Q=0.12; ESS14-P=0.779 Q=0.12; ESS16-P=0.368 Q=0.12; ESS17-P=0.368 Q=0.12; ESS22-P=0.368 Q=0.12; ESS25-P=2.5 Q=0.12; ESS29-P=0.877 Q=0.12; ESS30-P=2.5 Q=0.12; ESS31-P=0.368 Q=0.12; ESS32-P=0.657 Q=0.12 | 67.071 | 204.935 | 0.074 | 0.0523 | 10.821 | 4977685.117 |

**Mean**

| ESS7-P=0.885 Q=0.15; ESS8-P=0.488 Q=0.15; ESS9-P=0.460 Q=0.15; ESS11-P=0.460 Q=0.15; ESS13-P=0.809 Q=0.15; ESS16-P=0.460 Q=0.15; ESS25-P=2.372 Q=0.15; ESS29-P=0.460 Q=0.15; ESS30-P=2.5 Q=0.15; ESS31-P=0.460 Q=0.15; ESS32-P=0.815 Q=0.15 | 66.908 | 204.688 | 0.0739 | 0.0513 | 10.737 | 4939044.942 |

### σFSCABC

**Best**

| ESS7-P=0.885 Q=0.15; ESS8-P=0.488 Q=0.15; ESS9-P=0.460 Q=0.15; ESS11-P=0.460 Q=0.15; ESS13-P=0.809 Q=0.15; ESS16-P=0.460 Q=0.15; ESS25-P=2.368 Q=0.15; ESS29-P=0.460 Q=0.15; ESS30-P=2.5 Q=0.15; ESS31-P=0.460 Q=0.15; ESS32-P=0.814 Q=0.15 | 67.055 | 204.656 | 0.074 | 0.0513 | 10.674 | 4910064.964 |

**Worst**

| ESS7-P=1.449 Q=0.16; ESS10-P=0.490 Q=0.16; ESS14-P=0.962 Q=0.16; ESS15-P=0.490 Q=0.16; ESS18-P=0.490 Q=0.16; ESS25-P=2.355 Q=0.16; ESS27-P=0.490 Q=0.16; ESS28-P=0.490 Q=0.16; ESS30-P=2.5 Q=0.16; ESS31-P=0.490 Q=0.16; ESS32-P=0.496 Q=0.16 | 67.328 | 207.862 | 0.0774 | 0.0561 | 10.846 | 4989186.449 |

**Mean**

| ESS7-P=0.882 Q=0.15; ESS8-P=0.491 Q=0.15; ESS9-P=0.460 Q=0.15; ESS11-P=0.460 Q=0.15; ESS13-P=0.809 Q=0.15; ESS16-P=0.460 Q=0.15; ESS25-P=2.369 Q=0.15; ESS29-P=0.460 Q=0.15; ESS30-P=2.5 Q=0.15; ESS31-P=0.460 Q=0.15; ESS32-P=0.814 Q=0.15 | 67.067 | 205.015 | 0.0739 | 0.0514 | 10.75 | 4945024.959 |

### σABC

**Best**

| ESS7-P=0.885 Q=0.15; ESS8-P=0.488 Q=0.15; ESS9-P=0.460 Q=0.15; ESS11-P=0.460 Q=0.15; ESS13-P=0.808 Q=0.15; ESS16-P=0.460 Q=0.15; ESS25-P=2.368 Q=0.15; ESS29-P=0.460 Q=0.15; ESS30-P=2.5 Q=0.15; ESS31-P=0.460 Q=0.15; ESS32-P=0.814 Q=0.15 | 67.055 | 204.656 | 0.074 | 0.0513 | 10.674 | 4910064.964 |

**Worst**

| ESS7-P=1.449 Q=0.16; ESS10-P=0.490 Q=0.16; ESS14-P=0.962 Q=0.16; ESS15-P=0.490 Q=0.16; ESS18-P=0.490 Q=0.16; ESS25-P=2.355 Q=0.16; ESS27-P=0.490 Q=0.16; ESS28-P=0.490 Q=0.16; ESS30-P=2.5 Q=0.16; ESS31-P=0.490 Q=0.16; ESS32-P=0.496 Q=0.16 | 67.328 | 207.862 | 0.0774 | 0.0561 | 10.846 | 4989186.449 |

**Mean**

| ESS7-P=0.882 Q=0.15; ESS8-P=0.491 Q=0.15; ESS9-P=0.460 Q=0.15; ESS11-P=0.460 Q=0.15; ESS13-P=0.809 Q=0.15; ESS16-P=0.460 Q=0.15; ESS25-P=2.369 Q=0.15; ESS29-P=0.460 Q=0.15; ESS30-P=2.5 Q=0.15; ESS31-P=0.460 Q=0.15; ESS32-P=0.814 Q=0.15 | 67.067 | 205.015 | 0.0739 | 0.0514 | 10.75 | 4945024.959 |
5.6 Results and discussion

Table 5.5: Convergence and computation time of FSCABC and ABC algorithms

<table>
<thead>
<tr>
<th>Investigation category</th>
<th>FSCABC convergence</th>
<th>FSCABC computation time (s)</th>
<th>ABC convergence</th>
<th>ABC computation time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>After 182 iterations</td>
<td>310</td>
<td>After 257 iterations</td>
<td>548</td>
</tr>
<tr>
<td>II</td>
<td>After 274 iterations</td>
<td>492</td>
<td>After 396 iterations</td>
<td>762</td>
</tr>
</tbody>
</table>

characteristics of FSCABC and ABC optimization approaches for two investigation phases. The convergence results including computation time are tabulated in Table 5.5. Table 5.5 implies that the FSCABC algorithm converges after 182 and 274 iterations for investigation category I and investigation category II, respectively. In contrast, the ABC-based approach converges after 257 and 396 iterations for investigation category I and investigation category II, respectively. In other words, the FSCABC-based approach converges faster than the ABC algorithm. In real time, FSCABC and ABC approaches take about 310 s and 548 s, respectively, to locate the ESSs during investigation category I. For investigation category II, the FSCABC and ABC algorithms require around 492 s and 762 s, respectively, to allocate the ESSs on the distribution network.

5.6.5 Overall performance and ESS cost comparison using PQ and P injection approaches

Table 5.6 represents the performance indices of the system which are evaluated as per Section 5.5.3. Generally, $VPII > 1$ implies that the system has a good voltage profile. On the contrary, the higher values of $LLdI$, $PLsRI_P$, $PLsRI_Q$, and $PLsRI_T$ signify higher line loading, active power loss, reactive power loss, and total line loss, respectively.

The voltage profile improvement in terms of bus voltage, using the PQ injection approach over the P injection approach for investigation category I and investigation category II, is compared in Fig. 5.9(a) and Fig. 5.9(b), respectively. These suggest that the voltage profiles are improved for both investigation categories while using the PQ injection approach. From the viewpoint of point to point bus voltage measurement, the PQ injection approach provides improved voltage profiles at most of the buses for both investigation categories compared to the P injection approach. For instance, the voltage profile improvement is remarkable at buses 4 to 18, 20 to 22, 25 to 27, and 29 to
33 while using the PQ injection approach for investigation category I. For investigation category II, significant improvement in bus voltages is achieved through the PQ injection approach at buses 4 to 7, 9 to 18, and 22 to 31. The overall VPII is improved with the use of the PQ injection approach compared to the P injection approach for both investigation categories as evaluated in Table 5.6. For instance, the VPII = 1.037 for Case 4 (using the P injection approach) is improved to 1.079 during Case 2 (using the PQ injection approach) under investigation category I. On the other hand, Case 3 provides VPII = 1.082 which is higher than Case 5 (VPII = 1.064) during investigation category II.

Figure 5.10(a) and Fig. 5.10(b) compare the line loading characteristics using the PQ injection approach over the P injection approach for investigation category I and investigation category II, respectively. These suggest that the line loading during the PQ injection approach is minimized for both investigation categories compared to the P injection approach. The opposite characteristics are observed at some points on the curves such as at L9-L10, L13-L14, L22, L25-L26, and L30 for investigation category I and at L9-L10, L18, L24-L27, and L36 for investigation category II. The line loading minimization using the PQ injection approach is also realized from the LLdI value tabulated in Table 5.6. During investigation category I, the PQ injection approach provides LLdI = 0.822 (Case 2) which is 0.829 (Case 4) while using the P injection approach. On the other hand, the LLdI provided by the P injection approach is 0.819 (Case 5) which is minimized to 0.757 (Case 3) with the use of the PQ injection approach for investigation category II.
5.6 Results and discussion

Figure 5.9: Voltage profile comparison in terms of bus voltage using PQ and P injection approaches— (a) voltage profile comparison for investigation category I and (b) voltage profile comparison for investigation category II.

Figure 5.11 and Fig. 5.12 compare the active, reactive, and total line losses using the PQ injection and the P injection approaches for investigation category I and investigation category II, respectively. According to these illustrations, for both investigation categories, the PQ injection approach minimizes the real, reactive, and total line losses at most of the lines compared to the P injection approach. For both investigation categories in Fig. 5.11, although P injection approach minimizes losses at very few lines,
5. OPTIMAL ESS PLACEMENT AND SIZING USING PQ INJECTION APPROACH

![Figure 5.10](image)

**Figure 5.10:** Comparison of %line loading using PQ and P injection approaches— (a) line loading comparison for investigation category I and (b) line loading comparison for investigation category II.

The losses are minimized at most of the lines by the PQ injection approach. For example, the P injection approach provides lower amounts of active, reactive, and total line losses compared to the PQ injection approach at lines L2, L9, L22-L23, and L30 for investigation category I, while the PQ injection approach minimizes more losses at other
5.6 Results and discussion

Figure 5.11: Comparison of losses using PQ and P injection approaches for investigation category I—(a) comparison of active power loss, (b) comparison of reactive power loss, and (c) comparison of total line loss.

lines over the P injection approach. During investigation category II, the PQ injection approach minimizes higher amounts of active, reactive, and total line losses compared to the P injection approach at most of the lines except L9, L16, L18-L19, L22, L24, and
Figure 5.12: Comparison of losses using PQ and P injection approaches for investigation category II—(a) comparison of active power loss, (b) comparison of reactive power loss, and (c) comparison of total line loss.

L27. These minimization characteristics are also summarized in Table 5.6 as loss minimization indices which exhibit that Case 2 minimizes higher amount of active, reactive, and total line losses compared to Case 4, while Case 3 delivers lower amount of losses.
over Case 5.

**Table 5.7:** Performance improvement using the PQ injection approach compared to the P injection approach

<table>
<thead>
<tr>
<th>Evaluation parameters</th>
<th>P injection approach</th>
<th>PQ injection approach</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>For a uniform ESS size</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%VDevI</td>
<td>75.753</td>
<td>67.339</td>
<td>11.107%</td>
</tr>
<tr>
<td>%LLdT</td>
<td>241.128</td>
<td>221.849</td>
<td>7.995%</td>
</tr>
<tr>
<td>P_{Tot} (MW)</td>
<td>0.0905</td>
<td>0.084</td>
<td>7.182%</td>
</tr>
<tr>
<td>Q_{Tot} (MVar)</td>
<td>0.0683</td>
<td>0.0607</td>
<td>11.127%</td>
</tr>
<tr>
<td>Total line loss (MVA)</td>
<td>0.1134</td>
<td>0.1036</td>
<td>8.594%</td>
</tr>
<tr>
<td>For non-uniform ESS sizes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%VDevI</td>
<td>72.162</td>
<td>66.704</td>
<td>7.564%</td>
</tr>
<tr>
<td>%LLdT</td>
<td>240.039</td>
<td>204.375</td>
<td>14.858%</td>
</tr>
<tr>
<td>P_{Tot} (MW)</td>
<td>0.0894</td>
<td>0.0738</td>
<td>17.450%</td>
</tr>
<tr>
<td>Q_{Tot} (MVar)</td>
<td>0.0666</td>
<td>0.0521</td>
<td>21.772%</td>
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<tr>
<td>Total line loss (MVA)</td>
<td>0.1115</td>
<td>0.0903</td>
<td>18.966%</td>
</tr>
</tbody>
</table>

The overall performance improvement (expressed in percentage), using the PQ injection approach over the P injection approach, is estimated in Table 5.7. This suggests that the PQ injection approach achieves 11.107% improvement for voltage deviation, 7.995% for line loading, 7.182% for active power loss, 11.127% for reactive power loss, and 8.594% for total line loss over the P injection approach during investigation category I. On the contrary, during investigation category II, the proposed PQ approach attains 7.564% improvement for voltage deviation, 14.858% for line loading, 17.450% for active power loss, 21.772% for reactive power loss, and 18.966% for total line loss compared to the P injection approach. The overall comparison in terms of performance indices and total ESS unit cost is presented in Fig. 5.13. It is evident from the characteristics that the proposed PQ injection approach achieves higher performance improvement compared to the P injection approach for both investigation categories. However, the PQ injection approach requires higher distribution network investment cost, and the amount is higher for investigation category II than investigation category I.
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Figure 5.13: Performance and ESS cost comparison for various cases—(a) for investigation category I (b) for investigation category II.
5.7 Conclusions

This chapter has presented an effective strategy to allocate the distributed ESSs in distribution systems applying the FSCABC hybrid meta-heuristic optimization approach. The system performance is improved significantly by minimizing some key problems of distribution networks such as voltage deviation, power losses, and line loading through the application of the PQ injection approach. The obtained results from the FSCABC technique are verified by applying the ABC algorithm, and related indices are calculated to measure the performance improvement. The following conclusions can be made based on the investigations carried out in this study:

- The PQ injection approach successfully achieves 11.107% and 7.564% improvements in minimizing voltage deviation over the P injection approach for a uniform ESS size and non-uniform ESS sizes, respectively.

- For a uniform ESS size, the proposed PQ injection approach also achieves improvements in minimizing line loading and total line loss over the P injection approach by 7.995% and 8.594%, respectively. On the other hand, during non-uniform ESS size investigation, 14.858% improvement in line loading minimization and 18.966% improvement in total line loss reduction are achieved by the PQ injection approach compared to the P injection approach.

- The proposed PQ injection approach improves the network performances through increasing the distribution system investment cost. Hence, a tradeoff in relation to performance expectations and costs should be made.

Regarding future works, a sensitivity analysis regarding the optimal ESS allocation, optimal operation of ESSs taking into account RES uncertainty and the impact on ESS lifetime, detailed analysis regarding cost or financial impacts of the obtained ESS sizes, and inclusive ESS sizing can be investigated.
Chapter 5 references


Chapter 6

Optimal ESS Allocation and Sizing to Improve Performance and Power Quality of Distribution Networks

This chapter proposes a strategy for optimal allocation of distributed ESSs in distribution networks to simultaneously minimize voltage deviation, flickers, power losses, and line loading. The optimal ESS allocation is investigated through the PQ injection (considering a variable power factor on the dispatch of ESSs) and the results are compared in terms of performance and power quality improvements. An IEEE-33 bus distribution system (medium voltage), having a high influence of renewable (wind and solar) distributed generation, is used as the test network. The overall investigation is conducted for two distinct scenarios: (1) applying a uniform ESS size and (2) applying non-uniform ESS sizes. DIgSILENT PowerFactory is used for developing, analyzing, and testing the system models. The fitness-scaled chaotic artificial bee colony (FSCABC) optimization algorithm (a hybrid meta-heuristic technique) is applied to optimize parameters of the objective function. A Python script is used to automate simulation events in PowerFactory. The optimization results are verified through the application of the conventional artificial bee colony (ABC) algorithm. Detailed simulation results
6.1 Introduction

Today’s power systems undergo a period of change caused by various correlated issues such as integration of renewable resources [1–4], management of the increasing demand [5–8], power quality requirements [9, 10], power congestion [11], greenhouse gas (GHG) reduction [12], network expansion [13], and power system reliability [9, 10]. Energy storage systems (ESSs) are growingly being integrated in distribution networks to provide various advantages related to economic, technical, and environmental issues [14, 15]. These include facilitation of renewable energy source (RES) integration [16–18], load shifting [19–22], load levelling [23] and peak shaving [24], planning of distributed generation [25], RES energy time-shifting [26], minimization of voltage deviation [27], frequency regulation [11, 28], power quality improvement [11, 29, 30], overall cost reduction [31, 32] and profit maximization [11, 33], network expansion [34, 35], GHG reduction [36–38], operating reserves [11, 39], and network reliability [40]. However, the benefits from the allocation of ESSs cannot be achieved if they are misplaced or misused in distribution networks [41].

Distribution network service providers consider asset management as a crucial task to ensure safe and reliable operation of networks. However, the fulfilment of this target can increase the overall network cost. This cost could comprise network reinforcement for voltage and thermal stability which can significantly affect electricity prices. Voltage profile improvement and flicker disturbance minimization are also crucial for maintaining the network power quality. Therefore, the motivation of this study is to provide distribution system operators with a low cost solution for better asset management practice as well as maintaining power quality. As the implementation of utility-scale ESSs involves considerable capital investment, their optimal placement in distribution networks to achieve expected performance improvements is challenging. From this viewpoint, optimal allocation of ESSs is addressed in several studies [11, 15, 27, 30–32, 34, 42–51].
A comprehensive review on ESS allocation, sizing, operation, and power quality for mitigating various issues of distribution networks is presented in [14]. In [15], an optimal placement of ESSs is undertaken in an IEEE-33 bus distribution network using the ABC algorithm. The targets of the study is to simultaneously minimize the voltage deviation, line losses, and line loading including ESS investment cost. In [15], ESS sizing is accomplished through the injection of P to the network i.e. by applying a unity power factor (p.f.) approach on the dispatch of ESSs. Furthermore, the particle swarm optimization (PSO) algorithm is employed to justify the optimal results attained from the ABC approach.

A multi-objective ESS placement is accomplished in [42] for both distribution and transmission networks. On the distribution side, the optimal size of ESSs is evaluated for addressing peak load shaving and load curve smoothing. A sensitivity analysis is performed on the transmission side through economic dispatch, time domain power flow, and using complex-valued neural networks to place the ESSs. In [43], an optimal distributed ESS planning is proposed for soft open points-based distribution network scenarios. In that study, the reactive power capability of distributed generators (DGs) is embedded through network reconfiguration and a mixed-integer second order cone programming (MISOCP) model is employed to solve the problem. An optimal ESS allocation problem embedded with network reconfiguration (in an RES-integrated distribution network) is formulated in [31] to minimize overall system costs. The study employs a mixed-integer linear programming (MILP) approach to address the problem.

A network-aware technique, for the control and planning of ESSs in a distribution network (RES-integrated) is proposed in [45] to minimize operational and investment costs. Reference [46] explores the impact of ESS configuration and location on voltage profiles and power losses as well as utilization of ESSs in a feeder of low voltage (LV) distribution networks. Reference [34] proposes an optimal placement of distributed community-based ESSs to gain some distribution network benefits. The benefits are achieved from peaking photovoltaic (PV) generation, energy loss reduction, energy arbitrage, Var support, emission reduction, and network upgrade deferral.

A MILP strategy is proposed in [11] to maximize the overall profit of using distributed ESSs in distribution systems. The study provides a frequency regulation service through
controlling active and reactive powers and achieves energy price arbitrage, network congestion management, and energy reserve. In [47], the voltage fluctuation problems of PV-integrated LV networks are minimized through ESS allocation by employing a genetic algorithm (GA)-based approach combined with simulated annealing. On the other hand, a GA-based optimization strategy (bi-level) is applied in [48] for mitigating the same problem. Again in [30], the allocation of distributed ESSs is performed for minimizing both network losses and the energy cost in relation to congestion management and external grid, and providing voltage supports. The study employs an alternating direction strategy to multipliers for obtaining the solution of the problem.

Optimal ESS sizing and allocation are performed and validated through a mathematical modeling and optimal power flow (OPF) approach in [49]. In [50], a game-theory-based multi-agent strategy is proposed for optimal ESS placement to minimize the risk of energy transaction processes for energy agents. In [51], optimal ESS placement in a LV distribution network is performed to prevent over- and under-voltages and minimize overall network costs (regarding ESS and network losses), by employing clustering and sensitivity analysis and a multi-period OPF approach.

In [27], a cost-based optimization technique by MATLAB is employed for optimal distributed ESS placement and operation to improve generation and load hosting capability. Consequently, peak demand and power loss are minimized through the achievement of good voltage regulation. In [32], optimal ESS allocation is accomplished through GA (integrated with linear-programming) and a sequential MCS to maximize distribution network benefits by minimizing the costs of ESS installation, system upgrade, maintenance, interruption, and energy losses. In [44], GA hybridized with a linear programming solver, MATLAB optimization toolbox, and a sequential MCS are used for optimal ESS allocation and sizing. In that research, the distribution system benefits are maximized while managing loads, and minimizing of net present value (NPV) and overall costs.

Although various issues related to distribution networks are addressed in the above-mentioned literature, very few research [15] focus on power loss reduction and minimization of line loading as well as voltage deviation, where no studies investigate the minimization of flicker disturbance to the network. However, optimal solutions combining these parameters together are necessary to improve network performance and power
quality and can be obtained through optimal distributed ESS allocation. The importance of power quality for smart grid perspective is discussed in [52]. An ESS also has the capability to improve power quality [53]. Wind DGs emit flicker to the network [54, 55] significantly, which is an important issue for power quality management [56]. In [57], an ESS (supercapacitor) is used to alleviate the voltage flicker due to integration of wind generators. Although the ESS has the capability to mitigate flicker [57], this issue is not addressed by any of the above research. This research has adopted this requirement.

In the aforementioned literature, various modeling and optimization approaches (single and hybrid) are used for the optimal allocation of ESSs [11, 15, 27, 30–32, 34, 42–51]. This research applies a hybrid meta-heuristic optimization approach, the FSCABC algorithm, for optimal ESS allocation. Being robust and simple, the ABC algorithm has triple search capability (done by three types of bees) for solving multi-dimensional and complex combinatorial optimization problems [58–60]. The hybrid FSCABC approach eliminates the trapping problem of ABC algorithm in local optima and improves its performance [61–63].

In this research, a comprehensive investigation is conducted for optimal allocation of ESSs in an IEEE-33 bus distribution network. DIgSILENT PowerFactory is utilized for developing system models and analysis of the proposed system. The FSCABC optimization approach is used for optimization and python programming language is employed for controlling the system models as well as facilitating optimization. The key contributions of this chapter are outlined as follows:

• The optimal allocation of ESSs is investigated focusing on performance and power quality improvements as well as cost minimization. For performance improvement, minimization of line loading as well as active and reactive power losses are targeted, while flicker minimization and voltage profile improvement are addressed for power quality improvement. The studies related to ESS placement such as [30, 46, 51] have not simultaneously considered these parameters. Reference [15] considers some of these parameters; however, a unity p.f. approach on the ESS dispatch is applied while this research considers variable p.f. conditions. Furthermore, the flicker disturbance factor minimization is investigated in this study, which is not addressed in any of the literature discussed above.
6.2 Modeling of the ESS

The performance and power quality indices are estimated to monitor the performance and power quality improvements through the proposed ESS allocation. In addition, new indices for flicker minimization are introduced regarding continuous, switching, and overall network flickers.

Overall investigation for ESS allocation is carried out through PQ injections in two distinct phases: (1) applying a uniform ESS size, and (2) applying non-uniform ESS sizes. The results obtained from these investigations are analyzed and compared. Moreover, results obtained from FSCABC optimization approach are verified using an ABC algorithm.

6.2 Modeling of the ESS

The utility-scale ESSs are selected based on their technical characteristics, various performance factors, and applications [14, 64–67]. From the viewpoint of ESS cost, the UltraBattery (also called advanced lead-acid battery) is chosen in this study similar to [15]. Although the UltraBattery is considered as the ESS technology, the ESS model (developed by [15]) is generic and can be utilized for other ESS technologies.

The ESS model is subject to prerequisites of (6.1) to (6.7) in time $t$ (indexed $1, \ldots, NT$) [15]:

$$0.2 \leq SOC_g^{ESS} \leq 0.9 \quad (6.1)$$

$$P_{t}^{ESS,c} = \max \left\{ P_{ESS-min}^{c}, \frac{E_{t}^{ESS} - S_{ESS-max}^{ESS}}{\eta_c} \cdot \Delta t \right\} \quad (6.2)$$

$$P_{t}^{ESS,d} = \min \left\{ P_{ESS-max}^{d}, \frac{(E_{t}^{ESS} - S_{ESS-min}^{ESS}) \eta_d}{\Delta t} \right\} \quad (6.3)$$

Charging mode:

$$E_{t+1}^{ESS,c} = \min \left\{ E_t^{ESS} - \Delta t \cdot P_{t}^{ESS,c} \frac{\eta_c}{\eta_d}, S_{ESS-max} \right\} \quad (6.4)$$

$$P_{t}^{ESS,c} \leq P_{t}^{ESS} \leq P_{t}^{ESS,d} \quad (6.5)$$

Discharging mode:

$$E_{t+1}^{ESS} = \max \left\{ E_t^{ESS} - \Delta t \cdot P_{t}^{ESS,d} \frac{1}{\eta_d}, S_{ESS-min} \right\} \quad (6.6)$$
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\[ P_t^{ESS,e} \leq P_t^{ESS} \leq P_t^{ESS,d} \quad (6.7) \]

where,

- The ESS should control P in both ways and a priority for P and Q is required to fulfil \( S_{app} = \sqrt{P^2 + Q^2} \). The \( SOC_g^{ESS} \) is subject to (6.1) [68] and \( SOC_g^{ESS} = 1 \) and \( SOC_g^{ESS} = 0 \) indicate that the ESS is fully charged and discharged, respectively.

- Equation (6.2) and Equation (6.3) represent the maximum charging and minimum discharging rates, respectively.

- Equation (6.4) and Equation (6.5) limit the minimum energy stored to the ESS and charging power of the ESS, respectively. Equation (6.6) and Equation (6.7) restrict the maximum energy released from the ESS and power discharged by the ESS, respectively.

6.3 Formulation of the problem

6.3.1 Objective function

The objective function of the proposed placement problem is presented in (6.8) and formulated by means of (6.9) to (6.20) [15, 56, 69]. This is mainly a cost function representing the costs associated with network power quality (voltage deviation and network flickers), performance (power losses and line loading), and ESS units. This function comprises important cost factors in the category of power quality cost \( (C_{PQuality}) \), performance cost \( (C_{Performance}) \), and ESS cost \( (C_{ESS}) \), where all the factors are weighted equally with \( \gamma_{VD} = \gamma_{flicker} = \gamma_{PL} = \gamma_{LL} = \gamma_{ESS} = 1 \).

\[
\mathcal{J}(C_{F_i}^{OBJ}) = \min \left\{ \sum_n \left( C_{n}^{VD} + \gamma_{flicker} C_{n}^{flicker} \right) + \sum_l \left( C_l^{PL} + \gamma_{LL} C_l^{LL} \right) \right. \\
+ \left. \left( \frac{C_{ESS}^{ESS}}{C_{UT}} \right) \right\} 
\]

(6.8)
6.3 Formulation of the problem

where,

\[ C_{VD}^n = \left( \sum_{n=1}^{N} |V_{\text{target}} - V_B^n(S_{ESS}^n, S_{ESSQ}^n, \lambda_n^n)| \right) \cdot \Gamma_{VD} \]  
\( (6.9) \)

\[ C_{\text{flicker}}^n = \left( \sum_{n=1}^{N} P_{FC}^n + P_{FS}^n \right) \cdot \Gamma_{\text{flicker}} \]  
\( (6.10) \)

\[ P_{FC}^n = P_{SC}^n = P_{LT}^n = c_F(\psi_k, V_n) \cdot S_{WDG}^{\text{grid}}(S_{ESS}^n, S_{ESSQ}^n, \lambda_n^n) \]  
\( (6.11) \)

\[ P_{FS}^n = P_{STS}^n + P_{LTS}^n \]  
\( (6.12) \)

\[ P_{STS}^n = 18 \cdot N^{0.31} \cdot k_{step} \cdot (\psi_k) \cdot S_{WDG}^{\text{grid}}(S_{ESS}^n, S_{ESSQ}^n, \lambda_n^n) \]  
\( (6.13) \)

\[ P_{LTS}^n = 8 \cdot N^{0.31} \cdot k_{step} \cdot (\psi_k) \cdot S_{WDG}^{\text{grid}}(S_{ESS}^n, S_{ESSQ}^n, \lambda_n^n) \]  
\( (6.14) \)

\[ C_{PL}^n = \sqrt{(P_{LT}^n(S_{ESS}^n, S_{ESSQ}^n, \lambda_n^n))^2 + (Q_{LT}^n(S_{ESS}^n, S_{ESSQ}^n, \lambda_n^n))^2} \cdot \Gamma_{PL} \]  
\( (6.15) \)

\[ P_{LT}^n(S_{ESS}^n, S_{ESSQ}^n, \lambda_n^n) = \sum_{i=1}^{M} P_{L}(i,j) = \sum_{i=1}^{M} \left( R_{L}^i(i,j) \cdot \frac{P_{L}^2 + Q_{L}^2}{|V_B^n(S_{ESS}^n, S_{ESSQ}^n, \lambda_n^n)|^2} \right) \]  
\( (6.16) \)

\[ Q_{LT}^n(S_{ESS}^n, S_{ESSQ}^n, \lambda_n^n) = \sum_{i=1}^{M} Q_{L}(i,j) = \sum_{i=1}^{M} \left( X_{L}^i(i,j) \cdot \frac{P_{L}^2 + Q_{L}^2}{|V_B^n(S_{ESS}^n, S_{ESSQ}^n, \lambda_n^n)|^2} \right) \]  
\( (6.17) \)

\[ C_{LL}^l = \sum_{i=1}^{M} \% LL_l^{ESS}(S_{ESS}^n, S_{ESSQ}^n, \lambda_n^n) \cdot \Gamma_{LL} \]  
\( (6.18) \)

\[ \% LL_l^{ESS}(S_{ESS}^n, S_{ESSQ}^n, \lambda_n^n) = \left( \frac{S_L^{ESS}}{S_L^{\text{rated}}} \right) \times 100 \]  
\( (6.19) \)

The total ESS unit cost is estimated by (6.20):

\[ C_{UT}^{ESS} = \sum_{n=1}^{K} S_{ESS}^n \cdot C_{UU} \]  
\( (6.20) \)

In the above-mentioned equations, \( \Gamma_{VD} = 0.142 \) $ p.u. \ [15, 27], \( \Gamma_{\text{flicker}} = 0.142 \) $ p.u. (considered same as the voltage deviation rate), \( \Gamma_{PL} = 0.503 \) $ p.u. \ [15, 70], \( \Gamma_{LL} = 50.3471 \) c/kWh \ [15, 70], \( V_{\text{target}} = 1 \) p.u.. Furthermore, the \( C_{UU} = 460 \) $/kWh taking into account the UltraBattery application regarding commercial and industrial
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energy management [15, 71].

6.3.2 Constraints of the objective function

The objective function of (6.8) is subject to (6.21) to (6.31) along with the ESS model equations as defined in (6.1) to (6.7) [15]:

\[
P_{i}^{\text{gen}} + \sum_{j \in J^+} (P_{j \rightarrow i}^{\text{del}}) = P_{i}^{\text{con}} + \sum_{k \in J^-} (P_{i \rightarrow k}^{\text{del}}) \quad (6.21)
\]

\[
Q_{i}^{\text{gen}} + \sum_{j \in J^+} (Q_{j \rightarrow i}^{\text{del}}) = Q_{i}^{\text{con}} + \sum_{k \in J^-} (Q_{i \rightarrow k}^{\text{del}}) \quad (6.22)
\]

\[
V_{\min} < |V_{Bn-1}| < V_{\max} \quad (6.23)
\]

\[
P_{\text{ESS}-\min} \leq P_{\text{ESS}}^{n} \leq P_{\text{ESS}-\max} \quad (6.24)
\]

\[
S_{l-1} < S_{l}^{\max} \quad (6.25)
\]

\[
\lambda_{n}^{\text{ESS}} = \begin{cases} 0 & \text{if the ESS is active} \\ 1 & \text{otherwise} \end{cases} \quad (6.26)
\]

\[
S_{n}^{\text{ESSP}} = \begin{cases} \text{Assign} & \text{if } \lambda_{n}^{\text{ESS}} = 0 \\ 0 & \text{if } \lambda_{n}^{\text{ESS}} = 1 \end{cases} \quad (6.27)
\]

\[
S_{n}^{\text{ESSQ}} = \begin{cases} \text{Assign} & \text{if } \lambda_{n}^{\text{ESS}} = 0 \\ 0 & \text{if } \lambda_{n}^{\text{ESS}} = 1 \end{cases} \quad (6.28)
\]

\[
p_{\text{ESS}-\min} < p_{\text{ESS}}^{n} < p_{\text{ESS}-\max} \quad (6.29)
\]

\[
P_{t}^{\text{ESS},c} \leq P_{t}^{\text{ESS}} \leq P_{t}^{\text{ESS},d} \quad (6.30)
\]

\[
E_{\text{ESS}-\min} < E_{\text{ESS}} < E_{\text{ESS}-\max} \quad (6.31)
\]

where,

- The active and reactive power balances of ith bus are ensured by (6.21) and (6.22), respectively [15].
- Equation (6.23) signifies the voltage constraint of each bus [15].
Equation (6.24) guarantees the application of a p.f. limit (with in the range 0.95 to 1 [72]) on the dispatch of ESSs.

Equation (6.25) safeguards the line such that the line loading does not go beyond the maximum limit ($SL_l^{max}=80\%$) to ensure the thermal stability of cables [15].

The ESS allocation constraints are denoted by (6.26) to (6.28).

Equations (6.29) to (6.31) ensure that the ESS power or energy will not surpass their designated limits during charging and discharging actions. Furthermore, the ESS operation within the specified SOC limits is ensured by (6.1) to (6.7) [15].

6.4 FSCABC optimization and proposed approaches

6.4.1 FSCABC optimization approach

In this research, the grid-connected ESS allocation problem is optimized by the application of FSCABC algorithm whose overall steps are depicted in Fig. 6.1. The main limitation of the ABC optimization approach is the possibility of being trapped in local optima while global optimization is sought [61–63]. The problem can be resolved by combining two well-known techniques- (1) the fitness scaling technique and (2) the chaotic technique [62, 63]. A power-rank scaling technique is proposed for fitness scaling, which combines both power and rank strategies as given below:

$$fit_i^{scale} = \frac{r_{b-i}^m}{\sum_{i=1}^{SN} r_{b-i}^m}$$ (6.32)

where, $r_{b-i}$ = the rank of $i$th individual bee, $SN$ = the number of food source, and $m$ = the exponential value for power computation.

The chaotic search is delineated by the logistic function of (6.33).

$$x_{chao-i}^{n+1} = \mu x_{chao-i}^n (1 - x_{chao-i}^n), \quad i = 1, 2, ..., SN$$ (6.33)

where, $n$ = the iteration number, $x_{chao-i}^n$ = the $i$th chaotic variable, and $\mu^{BIF}$ = the bifurcation parameter of the system with $\mu^{BIF} \in [0, 4]$. The chaotic behaviour is revealed with $\mu^{BIF} = 4$, $x_{chao-i}^0 \in (0, 1)$, and $x_{chao-i}^0 \notin (0.25, 0.5, 0.75)$. 

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In the initialization phase, the colony size \((C_oS)\) of solutions \(x_{ij}(i = 1, 2, ..., SN; j = 1, 2, ..., D)\) \((D = \text{problem dimension})\) is ascertained with the number of employed bees \((N_E)\) and the number of onlooker bees \((N_O)\), while fulfilling \(C_oS = N_E + N_O\). The population is initialized with \(j = 0\) as given in (6.34).

\[ x_{i0} = lb + \psi_{ij}^{RAND} (ub - lb), \quad i = 1, 2, ..., SN \quad (6.34) \]

where, \(ub\) = the upper bound, \(lb\) = the lower bound, and \(\psi_{ij}^{RAND}\) = a random number
6.4 FSCABC optimization and proposed approaches

in the range $[0, 1]$. By utilizing (6.35), each employed bee travels from one old position $x_{ij}$ to new candidate position $v_{ij}$:

$$v_{ij} = x_{ij} + \Phi_{ij}^{RAND} (x_{ij} - x_{kj})$$  (6.35)

In (6.35), $k \in 1, 2, .., SN$ and $j \in 1, 2, .., D$ are randomly selected and $k$ has to be dissimilar from $i$, where, $\Phi_{ij}^{RAND}$ = a random uniform number in the range [-1, 1]. If the new location value $v_{ij}$ is better than $x_{ij}$, then $x_{ij}$ is replaced with updated $v_{ij}$, otherwise $x_{ij}$ is preserved unchanged. The fitness values of the food sources of employed bees ($fit^{FS}_i$) and the food source probability ($p^{FS}_i$) are computed as per (6.36) and (6.37), respectively, where, $f(x_i)^{OBJ}$ indicates the values of an objective function to be optimized.

$$fit^{FS}_i = \begin{cases} 
1 + f(x_i)^{OBJ}, & f(x_i)^{OBJ} \geq 0 \\
1 + |f(x_i)^{OBJ}|, & f(x_i)^{OBJ} < 0 
\end{cases}$$  (6.36)

$$p^{FS}_i = \frac{fit^{FS}_i}{\sum_{j=1}^{SN} fit^{FS}_j}$$  (6.37)

Depending on the value of $p^{FS}_i$, the onlooker bee determines a food source by utilizing a roulette wheel selection approach and then, this new location is found by (6.38), where, $\omega_i^{EmB} = \text{weight coefficient in relation to employed bee information.}$

$$v_{ij} = x_{ij} + \omega_i^{EmB} \Phi_{ij}^{RAND} (x_{ij} - x_{kj})$$  (6.38)

As the parameter $\Phi_{ij}^{RAND}$ is the key factor for convergence in ABC [62], the chaotic sequence of this parameter is described by (6.39) and used into (6.35) & (6.38).

$$\Phi_{ij}^{chaos} = 2 \times [4\Phi_{ij}^{RAND} (1 - \Phi_{ij}^{RAND})] - 1$$  (6.39)

In scout bee phase, the discarded solutions are improved and replaced by a new solution $x_{ij}^{chaos}$ as defined in (6.40).

$$x_{ij}^{chaos} = \text{MIN} (x_{ij}) + \varphi_{ij} [\text{MAX} (x_{ij}) - \text{MIN} (x_{ij})]$$  (6.40)

where, $\text{MAX}(x_{ij}) = \text{MAX} \{x_{1j}, x_{2j}, ..., x_{Nj}\}$ and $\text{MIN}(x_{ij}) = \text{MIN} \{x_{1j}, x_{2j}, ..., x_{Nj}\}$, and $\varphi_{ij}^{RAND}$ = a random number in the range [-1, 1]. Similar to parameter $\Phi_{ij}^{RAND}$, the
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A chaotic sequence of $\phi_{ij}^{RAND}$ is defined by (6.41) and utilized within (6.40).

$$\phi_{ij}^{chaos} = 4\phi_{ij}^{RAND} \left(1 - \phi_{ij}^{RAND}\right)$$  (6.41)

**Table 6.1:** Summary of FSCABC optimization variables and parameters

<table>
<thead>
<tr>
<th>Type</th>
<th>Parameters/variables</th>
<th>Description/settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input parameters</td>
<td>$V_{rated}, P_L^{i,j}, X_L^{i,j}, P, Q, P^{-F}, Q^{-F}, S_{wind}, S_{PV-max}, S_{PV-op}$ and $S_{ESS-nom}$</td>
<td>Required for the network model.</td>
</tr>
<tr>
<td>Output parameters</td>
<td>$C_{VDn}, C_{LLl}, C_{PLl}$ and $C_{ESSUT}$</td>
<td>Required for the objective function.</td>
</tr>
<tr>
<td>Decision variables</td>
<td>$S_{ESSP_n}$</td>
<td>This variable determines the amount of P to be injected by the ESSs in the network.</td>
</tr>
<tr>
<td></td>
<td>$S_{ESSQ_n}$</td>
<td>This variable determines the amount of Q to be injected by the ESSs in the network.</td>
</tr>
<tr>
<td></td>
<td>$\lambda_{ESS_n}$</td>
<td>This variable determines the position of ESSs in the network.</td>
</tr>
<tr>
<td>FSCABC parameters</td>
<td>$\mu_{BIF}, \psi_{ij}^{RAND}, \Phi_{ij}^{RAND}, \phi_{ij}^{RAND}$ and $x_{chaos-i}$</td>
<td>Settings: $\mu_{BIF} \in [0, 4], \psi_{ij}^{RAND} \in [0, 1], \Phi_{ij}^{RAND} \in [-1, 1], \phi_{ij}^{RAND} \in [-1, 1], x_{chaos-i} \in (0, 1)$, and $x_{chaos-i} \in {0.25, 0.5, 0.75}$.</td>
</tr>
<tr>
<td></td>
<td>$D, C_o, S, L_{trial}$ and $I_{max}$</td>
<td>Settings: $D = 3 = N_D, C_oS = 100, SN = C_oS/2 = population size, L_{trial} = 60, and I_{max} = 1000$.</td>
</tr>
<tr>
<td>FSCABC bounds</td>
<td>For $S_{ESSP_n}$: $lb_1$ and $ub_1$</td>
<td>Settings: $lb_1 = 0.1$ MW and $ub_1 = 2.5$ MW for investigation phase-I; $lb_1 = 0.1$ MW and $ub_1 = 3$ MW for investigation phase-II.</td>
</tr>
<tr>
<td></td>
<td>For $S_{ESSQ_n}$: $lb_2$ and $ub_2$</td>
<td>Settings: $lb_2 = 0.1$ MVar and $ub_2 = 1.5$ MVar for both investigation phase-I and investigation phase-II.</td>
</tr>
<tr>
<td></td>
<td>For $\lambda_{ESS_n}$: $lb_3$ and $ub_3$</td>
<td>Settings: $lb_3 = 0$ and $ub_3 = 1$.</td>
</tr>
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</table>

6.4.2 Proposed approach

The methodology for the proposed ESS allocation is depicted in Fig. 6.2. After inserting the essential data to all components of a distribution system, the FSCABC parameters are initialized. Optimization variables and parameters are summarized in Table 6.1. Some important steps in the distribution network model, such as feeder load scaling, instigating a voltage dependency of loads, applying the time-variant characteristics (as given in [15]) to the loads, wind, and solar DGs, are accomplished. The flicker disturbance is instigated by the wind DGs which is distributed throughout the network. Afterwards, the optimal placement problem is formulated to minimize the sum of $C_{VDn}$.
6.4 FSCABC optimization and proposed approaches

Figure 6.2: Flowchart of the proposed optimal ESS allocation approach.

\[ C_{n}^{\text{flicker}}, C_{l}^{\text{PL}}, C_{l}^{\text{LL}}, \text{and } C_{UT}^{\text{ESS}} \] in two distinct phases- (1) investigation phase-I: applying a uniform ESS size and (2) investigation phase-II: applying non-uniform ESS sizes.

The ESSs are located throughout the network using the decision variable \( \lambda_{n}^{\text{ESS}} \), where \( \lambda_{n}^{\text{ESS}} = 0 \) represents an ESS of \( n \)th bus is active and \( \lambda_{n}^{\text{ESS}} = 1 \) signifies the ESS is inactive. The ESS size (MVA) in a bus is determined through decision variables \( S_{n}^{\text{ESSP}} \) (MW) and \( S_{n}^{\text{ESSQ}} \) (MVar). The \( S_{n}^{\text{ESSP}}, S_{n}^{\text{ESSQ}}, \text{and } \lambda_{n}^{\text{ESS}} \) are generated randomly within the nominated ranges (in the ranges \( P = 0.1 \text{ MW to } 2.5 \text{ MW}, Q = 0.1 \text{ MVar to} \)
6. OPTIMAL ESS ALLOCATION AND SIZING TO IMPROVE PERFORMANCE AND POWER QUALITY OF DISTRIBUTION NETWORKS

1.5 MVar for investigation phase-I and $P = 0.1$ MW to 3 MW, $Q = 0.1$ MVar to 1.5 MVar for investigation phase-II) and injected to the network targeting the distributed placement of maximum number of ESSs with smaller sizes. The ESS size determination is subject to $lb_1, lb_2, lb_3, ub_1, ub_2, ub_3$, ESS string size, inverter specifications, AC and DC bus size, and transformer size. Furthermore, for sizing, a variable p.f. (not less than 0.95) is employed on the dispatch of an ESS. Finally, the optimal values of $S_{ESSP}^n$, $S_{ESSQ}^n$, and $\lambda_{ESS}^n$ are obtained by the FSCABC optimization approach while fulfilling the necessary constraints.

6.5 Testing and assignment of factors and indices for performance improvement

This section explores the distribution network where the approach is tested, assignment of essential factors regarding flicker assignment, load scaling of the feeder, and creating voltage dependency. This section also describes the required indices to assess the improvements of system performance and power quality.

![Figure 6.3: Single-line diagram of the proposed distribution network model.](image-url)
6.5 Testing and assignment of factors and indices for performance improvement

Table 6.2: Information of the proposed distribution network model [15]

<table>
<thead>
<tr>
<th>Model specification</th>
<th>Model data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base MVA</td>
<td>10 MVA</td>
</tr>
<tr>
<td>Substation voltage</td>
<td>12.66 kV</td>
</tr>
<tr>
<td>PV1 and PV3 are allocated on bus5 and bus21, respectively</td>
<td>size = 400 kVA</td>
</tr>
<tr>
<td>PV2 is installed on bus8</td>
<td>size = 500 kVA</td>
</tr>
<tr>
<td>WDG1, WDG2, WDG3, WDG4, WDG5, and WDG6 are placed on bus12, bus18, bus24, bus31, bus28, and bus33, respectively</td>
<td>size = 1 MVA</td>
</tr>
<tr>
<td>$S_{PV-op}$</td>
<td>85% of $S_{PV-max}$</td>
</tr>
<tr>
<td>$P^{T-F}$ (for feeder load scaling)</td>
<td>3.715 MW</td>
</tr>
<tr>
<td>$Q^{T-F}$ (for feeder load scaling)</td>
<td>2.3 MVar</td>
</tr>
</tbody>
</table>

6.5.1 Test distribution network

The IEEE-33 bus radial distribution system is used for testing of the proposed approach. The single line diagram of the distribution system is depicted in Fig. 6.3. The proposed system is modeled using DIgSILENT PowerFactory. The lines and buses are symbolized by the letter 'L' and the numbers 1 to 33, respectively, where L33 to L37 indicate tie lines and bus 1 represents the feeder. In this model, three solar DGs and six wind DGs are installed to create a scenario of high RES penetration. The wind DGs (WDGs), solar DGs (PVs), and loads are modeled using built-in templates within PowerFactory and the system data is taken from [15]. The overall model information is provided in Table 6.2.

6.5.2 Assignment of factors

6.5.2.1 Assignment of flicker disturbance:

The flicker coefficients of WDGs are assigned considering $v_a=10 \text{ m/s}$ as presented in Table 6.3 [54]. The flicker disturbance is generated for various $\psi_k$ values such as $30^\circ$, $50^\circ$, $70^\circ$, and $85^\circ$. It is assumed that during switching operations, a turbine starts-up at cut-in wind speed with $N_{10} = 3$ and $N_{120} = 30$. The flicker disturbance generated from a WDG is distributed throughout the network which affects the $S_{grid}^{n}$ of a bus $n$. 

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Table 6.3: Applied flicker coefficient values to wind DGs

<table>
<thead>
<tr>
<th>$\psi_k$</th>
<th>$c_F(\psi_k, \nu a)$</th>
<th>$k_{step}(\psi_k)$</th>
<th>$kv(\psi_k)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>30°</td>
<td>7.9</td>
<td>0.35</td>
<td>0.7</td>
</tr>
<tr>
<td>50°</td>
<td>6.6</td>
<td>0.34</td>
<td>0.7</td>
</tr>
<tr>
<td>70°</td>
<td>5.7</td>
<td>0.38</td>
<td>0.8</td>
</tr>
<tr>
<td>85°</td>
<td>7.3</td>
<td>0.43</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Maximum switching operations

$N_{10} = 3, N_{120} = 30$

6.5.2.2 Assignment of feeder load scaling and voltage dependency

The feeder loads are scaled using the instructions described in [15], while the loads of the system follow the IEEE-RTS model. The total active and reactive powers are estimated by applying a scale ($\Psi^{scale}$) and the voltage dependency of loads as denoted in (6.42) and (6.43), respectively [15]. The scaling of wind and solar DG outputs is performed using the characteristics provided in [15].

$$P = \Psi^{scale} \cdot P_0 \left[ aP \cdot \left( \frac{V^B_n}{V_{ref}} \right)^{e_{aP}} + bP \cdot \left( \frac{V^B_n}{V_{ref}} \right)^{e_{bP}} + (1-aP-bP) \cdot \left( \frac{V^B_n}{V_{ref}} \right)^{e_{cP}} \right]$$  \hspace{1cm} (6.42)

$$Q = \Psi^{scale} \cdot Q_0 \left[ aQ \cdot \left( \frac{V^B_n}{V_{ref}} \right)^{e_{aQ}} + bQ \cdot \left( \frac{V^B_n}{V_{ref}} \right)^{e_{bQ}} + (1-aQ-bQ) \cdot \left( \frac{V^B_n}{V_{ref}} \right)^{e_{cQ}} \right]$$  \hspace{1cm} (6.43)

where, $(1-aP-bP) = cP$, $(1-aQ-bQ) = cQ$, $aP = aQ = 0.4$, $bP = bQ = 0.3$, $cP = cQ = 0.3$, $e_{aP} = e_{aQ} = 0$, $e_{bP} = e_{bQ} = 1$, and $e_{cP} = e_{cQ} = 2$ [15].

6.5.3 Performance improvement indices of the system

6.5.3.1 Indices for voltage deviation and profile improvement

The voltage deviation of $n$th bus is calculated using $V^{max}$ and $V^{min}$ (assuming deviation limit=$\pm5\%$). The percent voltage deviation index ($%VDI$) is described by (6.44) [15].

$$%VDI = \sum_{n=1}^{N} \left( \frac{|V_{\text{rated}} - V_{n}^B|}{V_{\text{rated}}} \right) \times 100$$  \hspace{1cm} (6.44)
6.5 Testing and assignment of factors and indices for performance improvement

The overall voltage profile \((VP)\) and the index for voltage profile improvement \((VPII)\) of the system are described by (6.45) and (6.46), respectively [15], where \(VP_n\) is the voltage profile of \(n\)th bus and \(\sum_{n=1}^{N} \zeta_n = 1\).

\[
VP = \sum_{n=1}^{N} VP_n = \sum_{n=1}^{N} V_n^B s_n^L \zeta_n \quad (6.45)
\]

\[
VPII = \frac{VPw-ESS}{VPwo-ESS} \quad (6.46)
\]

6.5.3.2 Indices for flicker minimization

Flicker minimization indices \((FMI^{Cont}, FMI^{STS},\) and \(FMI^{LTS})\), for both continuous and switching operations, are defined according to IEC standard 61400-21 ((6.11), (6.13), and (6.14)) as presented in (6.47), (6.48), and (6.49).

\[
FMI^{Cont} = \frac{\sum_{n=1}^{N} P_n^{FC} - ESS}{\sum_{n=1}^{N} P_n^{FC} - base} \quad (6.47)
\]

\[
FMI^{STS} = \frac{\sum_{n=1}^{N} P_n^{ST} - ESS}{\sum_{n=1}^{N} P_n^{ST} - base} \quad (6.48)
\]

\[
FMI^{LTS} = \frac{\sum_{n=1}^{N} P_n^{LT} - ESS}{\sum_{n=1}^{N} P_n^{LT} - base} \quad (6.49)
\]

Total flicker minimization index is defined as:

\[
FMI^T = \frac{\sum_{n=1}^{N} (P_n^{FC} - ESS + P_n^{ST} - ESS + P_n^{LT} - ESS)}{\sum_{n=1}^{N} (P_n^{FC} - base + P_n^{ST} - base + P_n^{LT} - base)} \quad (6.50)
\]

The improvement index for relative voltage change \((RVCII)\) at 20 °C is defined as:

\[
RVCII = \frac{\sum_{n=1}^{N} d_n^{Sw} - ESS}{\sum_{n=1}^{N} d_n^{Sw} - base} \quad (6.51)
\]

where,

\[
\%d^{Sw} = 100 \cdot k_v(\psi_{k}) \cdot \frac{S^{WDG}}{S^{grid}} \quad (6.52)
\]
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6.5.3.3 Indices for power loss reduction

The indices for the reduction of line losses such as real, reactive, and total line losses ($PLRI^P$, $PLRI^Q$, and $PLRI^T$) are defined by (6.53), (6.54), and (6.55), respectively [15].

\[
PLRI^P = \frac{\sum_{l=1}^{M} P_{l}^{L-ESS}}{\sum_{l=1}^{M} P_{l}^{L-base}} \quad (6.53)
\]
\[
PLRI^Q = \frac{\sum_{l=1}^{M} Q_{l}^{L-ESS}}{\sum_{l=1}^{M} Q_{l}^{L-base}} \quad (6.54)
\]
\[
PLRI^T = \frac{\sum_{l=1}^{M} \sqrt{(P_{l}^{L-ESS})^2 + (Q_{l}^{L-ESS})^2}}{\sum_{l=1}^{M} \sqrt{(P_{l}^{L-base})^2 + (Q_{l}^{L-base})^2}} \quad (6.55)
\]

6.5.3.4 Line loading index

The line loading index ($LLI$) of (6.56) is computed using the percent line loading of $l$th line for base case ((6.57)) and after ESS placement ((6.19)) [15].

\[
LLI = \frac{\% LLT_{w-ESS}}{\% LLT_{wo-ESS}} = \frac{\sum_{l=1}^{M} \% LL_{l}^{ESS}}{\sum_{l=1}^{M} \% LL_{l}^{base}} \quad (6.56)
\]
\[
\% LL_{l}^{base} = \left( \frac{SL_{l}^{base}}{SL_{l}^{rated}} \right) \times 100 \quad (6.57)
\]

6.5.3.5 Power quality improvement index

The power quality index ($PQI$), after minimizing the voltage deviation and flicker disturbance through the ESS placement, can be defined as (6.58). The index for power quality improvement ($PQII$) can be defined as (6.59).

\[
PQI = \frac{VDI_{w-ESS}^w - ESS + \sum_{n=1}^{N} \left( P_{n}^{FCont-ESS} + P_{n}^{STS w-ESS} + P_{n}^{LTS w-ESS} \right)}{VDI_{wo-ESS}^w + \sum_{n=1}^{N} \left( P_{n}^{FCont-base} + P_{n}^{STS w-base} + P_{n}^{LTS w-base} \right)} \quad (6.58)
\]
\[
PQII = \frac{1}{PQI} \quad (6.59)
\]
6.6 Results and discussion

This section explores the impact of the proposed ESS placement in the distribution network regarding system power quality, system performance, and cost minimization. Optimal ESS locations are determined while minimizing the cost function at peak load condition. The performance analysis is conducted for three different case studies: (i) Case 1- base case (without ESSs), (ii) Case 2- placement of ESSs applying a uniform size, and (iii) Case 3- placement of ESSs applying non-uniform sizes. The ESS sizing is accomplished through PQ injection by the ESSs with a variable p.f. (not less than 0.95). The system results are presented in Table 6.4 and Table 6.5. This section also compares the optimization results achieved from FSCABC approach with ABC algorithm. In this study, ESS power rating (MVA) is taken into account as constant over one hour [15].

Table 6.4: ESS size and locations for various case studies

<table>
<thead>
<tr>
<th>Case studies</th>
<th>P (MW), Q (MVar), and locations of ESSs</th>
<th>Total ESS Size (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1-Without ESS allocation (base case)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Case 2-Distributed ESS allocation for a uniform ESS size</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs P = 1.269 Q = 0.417</td>
<td>12.022</td>
</tr>
<tr>
<td>Case 3-Distributed ESS allocation for non-uniform ESS sizes</td>
<td>ESS7-P=1.491 Q=0.231; ESS8-P=1.234 Q=0.231; ESS10-P=0.703 Q=0.231; ESS13-P=0.851 Q=0.231; ESS15-P=1.094 Q=0.231; ESS22-P=0.703 Q=0.231; ESS24-P=1.736 Q=0.231; ESS25-P=3 Q=0.231; ESS27-P=0.703 Q=0.231; ESS29-P=0.838 Q=0.231; ESS30-P=3 Q=0.231; ESS31-P=0.703 Q=0.231; ESS32-P=1.258 Q=0.231</td>
<td>17.572</td>
</tr>
</tbody>
</table>

Table 6.5: System results after a quantitative analysis for various cases of Table 6.4

<table>
<thead>
<tr>
<th>Case Details</th>
<th>%VDI</th>
<th>( \sum_{n=1}^{N} P^{FCont} )</th>
<th>( \sum_{n=1}^{N} P^{STS_w} )</th>
<th>( \sum_{n=1}^{N} P^{LTS_w} )</th>
<th>( \sum_{n=1}^{N} Q^{Sw} )</th>
<th>( pLT ) (MW)</th>
<th>( QLT ) (MVar)</th>
<th>%LLT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>82.707</td>
<td>5.454</td>
<td>4.808</td>
<td>4.363</td>
<td>29.357</td>
<td>0.107</td>
<td>0.083</td>
<td>269.024</td>
</tr>
<tr>
<td>Case 2</td>
<td>54.129</td>
<td>5.024</td>
<td>4.432</td>
<td>4.022</td>
<td>27.449</td>
<td>0.080</td>
<td>0.064</td>
<td>226.546</td>
</tr>
<tr>
<td>Case 3</td>
<td>51.205</td>
<td>4.891</td>
<td>4.300</td>
<td>3.902</td>
<td>26.743</td>
<td>0.060</td>
<td>0.042</td>
<td>201.322</td>
</tr>
</tbody>
</table>

6.6.1 Case study 1 - base case without ESS placement

Various parameter results obtained from the base case analysis (without ESS allocation) are presented in Table 6.5. The values of parameter \( \%VDI, \sum_{n=1}^{N} P^{FCont} \),
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\[ \sum_{n=1}^{N} P^{STS_w}, \sum_{n=1}^{N} P^{LTS_w}, P_{LT}, Q_{LT}, \text{ and } \%LLT \text{ are targeted to be optimized. In Case 2 and Case 3 of Table 6.5, a parameter value lower than the corresponding base value represents the performance improvement and vice-versa.} \]

6.6.2 Case study 2- placement of ESSs through uniform sizing approach

Results of optimal ESS allocation by applying uniform \( S_{n}^{ESSP} \) and \( S_{n}^{ESSQ} \) are presented in Table 6.4. The \( S_{n}^{ESSP} \), \( S_{n}^{ESSQ} \), and \( \lambda_{n}^{ESS} \) can be recognized in Table 6.4 by the ESS P (MW), ESS Q (MVar), and ESS number, respectively. For instance, P = 1.269 and Q = 0.417 of ESS7 indicate that an ESS of 1.269 MW and 0.417 MVar (total size = 1.336 MVA) is connected to bus7. Nine ESSs having a uniform size (1.336 MVA) are allocated on bus numbers 7, 9, 14, 24, 25, 29, 30, 31, and 32. Table 6.4 suggests that all parameters such as \( \%VDI, \sum_{n=1}^{N} P^{FCont}, \sum_{n=1}^{N} P^{STS_w}, \sum_{n=1}^{N} P^{LTS_w}, \sum_{n=1}^{N} \%d^{Sw}, P_{LT}, Q_{LT}, \text{ and } \%LLT \) are reduced compared to Case 1. The results of Case 2 parameters are obtained with a total ESS size of 12.022 MWh.

6.6.3 Case study 3- placement of ESSs through non-uniform sizing approach

The impact of optimal ESS placement, using the non-uniform ESS sizing approach, is analyzed and obtained results are presented in Table 6.5 (Case 3). During Case study 3, the \( S_{n}^{ESSP} \) is allotted non-uniformly to all ESSs, while the \( S_{n}^{ESSQ} \) is assigned uniformly to all ESSs. The \( S_{n}^{ESSP} \), \( S_{n}^{ESSQ} \), and \( \lambda_{n}^{ESS} \) can be recognized in Table 6.4 by the ESS P (MW), ESS Q (MVar), and ESS number, respectively. For instance, ESS7-P = 1.491 Q = 0.231 indicates that an ESS of 1.491 MW and 0.231 MVar (total size = 1.509 MVA) is allocated to bus7. Thirteen ESSs having non-uniform sizes are allocated on bus number 7, 8, 10, 13, 15, 22, 24, 25, 27, 29, 30, 31, and 32. Table 6.5 shows that all Case 3 parameters, e.g., \( \%VDI, \sum_{n=1}^{N} P^{FCont}, \sum_{n=1}^{N} P^{STS_w}, \sum_{n=1}^{N} P^{LTS_w}, \sum_{n=1}^{N} \%d^{Sw}, P_{LT}, Q_{LT}, \text{ and } \%LLT \) are further minimized compared to Case 2. However, a total ESS size of 17.572 MWh is required for Case 3, which indicates an augmentation in distribution system investment cost over Case 2 (12.022 MWh).
6.6 Results and discussion

6.6.4 Overall result analysis and comparison

6.6.4.1 Comparison in relation to voltage profiles

Figure 6.4: Voltage profiles of buses for various cases—(a) in terms of bus voltage and (b) in terms of $VP_n$.

6.6.4 Overall result analysis and comparison

6.6.4.1 Comparison in relation to voltage profiles

Figure 6.4(a) and Fig. 6.4(b) depict the voltage profiles of various cases in terms of bus voltage and $VP_n$, respectively. The feeder voltage profiles (in terms of feeder distance) for Case 1, Case 2, and Case 3 are displayed in Fig. 6.5, Fig. 6.6, and Fig. 6.7, respectively. According to these illustrations, both Case 2 and Case 3 provide improved voltage profiles compared to Case 1. However, Case 3 has improvements in voltage deviation compared to Case 2 such as at buses 5 to 13, 20 to 22, and 25 to 29. For
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Figure 6.5: Voltage profile of the network feeder for Case 1.

Figure 6.6: Voltage profile of the network feeder for Case 2.
6.6 Results and discussion

Figure 6.7: Voltage profile of the network feeder for Case 3.

instance, the voltage at bus 12 for Case 3 is 0.974 p.u., while this is 0.980 p.u. for Case 2. In contrast, Case 2 provides improved voltage at buses 16 to 18 and 31 to 33 compared to Case 3. Figure 6.6 and Fig. 6.7 indicate that the feeder voltage profiles have been significantly improved for Case 2 and Case 3 compared to Case 1 (Fig. 6.5). The improvement in feeder section L02-L22-L23-L24-L37-L29-L30-L31-L32 is significant for both cases compared to Case 1. The parameter $\%VDI$ also indicates the comparison of voltage deviations for various cases as given in Table 6.5. Overall, Case 3 ($\%VDI = 51.205$) provides a slightly better voltage profile than Case 2 ($\%VDI = 53.129$).

6.6.4.2 Comparison of flicker minimization characteristics

The characteristics for continuous and switching flickers (at various buses) of various cases are presented in Fig. 6.8(a) and Fig. 6.8(b), respectively. Both continuous and switching flicker characteristics have similar patterns, where higher flicker disturbances are observed at bus 18 and bus 33 compared to others. In contrast, the lowest flicker disturbance is noticed at bus 1. The values of flicker parameters such as $\sum_{n=1}^{N}PF^\text{Cont}$,
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Figure 6.8: Flicker comparison at various buses—(a) continuous flicker and (b) switching flicker.

Figure 6.9: Relative voltage change (%) during switching of WDGs for various cases.
Figure 6.10: (a) The short circuit power of buses for various cases and (b) impedance angle of buses for various cases.
Figure 6.11: (a) Network flicker comparison for various cases and (b) total flicker for various cases.
6.6 Results and discussion

\[ \sum_{n=1}^{N} P^{STSw}, \text{ and } \sum_{n=1}^{N} P^{LTSw} \] are reduced for Case 2 and Case 3, while Case 3 minimizes these disturbances better than Case 2 (as per Table 6.5). Relative voltage change (%) during switching of WDGs (for various cases) is depicted in Fig. 6.9. As referred to Table 6.5, the \[ \sum_{n=1}^{N} \%d^{Sw} \] for Case 1 is 29.357, while this reduced to 27.449 and 26.743 for Case 2 and Case 3, respectively.

Figure 6.10(a) and Fig. 6.10(b) compare the short circuit power \( S_{kn}^{k} \) and impedance angle \( \Omega_{kn}^{k} \) for various cases, respectively. The \( S_{kn}^{k} \) and \( \Omega_{kn}^{k} \) at various buses are slightly affected through PQ injection by the ESSs. For instance, the value of \( S_{k1}^{k} \) at bus 1 is 9094.344 MVA, 9099.133 MVA, and 9099.618 MVA for Case 1, Case 2, and Case 3, respectively. A change of about 500 kVA is observed in \( S_{k1}^{k} \) for Case 3 compared to Case 2. On the other hand, the value of \( \Omega_{k1}^{k} \) on the same bus (bus 1) is 84.231°, 84.176°, and 84.148° for Case 1, Case 2, and Case 3, respectively. Figure 6.11(a) compares flicker disturbances for various cases, while Fig. 6.11(b) exhibits the total flicker characteristics which is calculated based on total flicker of various buses. Figure 6.11 suggests that Case 3 minimizes the total flicker disturbance better than Case 2, while demanding a larger ESS installation (17.572 MWh) compared to Case 2.

6.6.4.3 Comparison of line losses and loading

The comparative performance of various cases in terms of real, reactive, and total line losses is presented in Fig. 6.12. As referred to in Fig. 6.12(a), Case 2 exhibits a higher active power loss at lines L3-L5, L8-L9, L16-L20, and L30, while a higher active power loss value is noticed at lines L13-L15, L22-L24, and L26-L29 for Case 3. The line L2 has the highest active power loss of 0.0186 MW and 0.0193 MW for Case 2 and Case 3, respectively. According to Fig. 6.12(b), L30 exhibits the highest reactive power loss of 0.0163 MVar for Case 2. Overall, Case 3 minimizes the active, reactive, and total power losses (0.060 MW, 0.042 MVar, and 0.075 MVA) compared to Case 2 (0.080 MW, 0.064 MVar, and 0.106 MVA) as per Table 6.5. Percent line loadings, with respect to individual line numbers, is represented in Fig. 6.13. For all cases, the loading of individual lines is below the maximum loading limit (80%). Significantly, a maximum loading of 41.513% is observed at L1 for all cases, while L2 has a loading of 27.824%, 23.357%, and 23.784% for Case 1, Case 2, and Case 3, respectively. The loading of all other lines varies closely.
Figure 6.12: Comparison of losses—(a) comparison of active power loss, (b) comparison of reactive power loss, and (c) comparison of total line loss.
6.6 Results and discussion

Figure 6.13: Percent line loading for various cases.

for Case 2 and Case 3. As referred to in Fig. 6.13 and Table 6.5, the overall line loading for Case 2 and Case 3 are reduced to 226.546% and 201.322%, respectively, compared to Case 1 (269.024%). These characteristics of line loading suggest that the system feeder has adequate surplus capacity to recover unexpected situations during outage through load sharing.

6.6.4.4 Statistical analysis of FSCABC approach with ABC algorithm

The same ABC approach given in [15] is utilized to justify the results obtained from the FSCABC algorithm. The overall modeling of ABC algorithm is demonstrated in Chapter 4, Section 4.4.1. The same settings ($D$, $C_0S$, $SN$, $L^{trial}$, and $I^{max}$) are used for both FSCABC and ABC approaches as displayed in Table 6.1. For both approaches, the optimization is executed 30 times and thereby the best, worst, and mean solutions of the objective function are obtained. Table 6.6 compares the optimization results obtained from both approaches along with the evaluation of standard deviations ($\sigma^{FSCABC}$ and $\sigma^{ABC}$). The smaller standard deviation signifies lower deviation among solutions obtained from 30 optimization runs. It is clear from the statistical analysis presented in Table 6.6 that the FSCABC technique is successful in obtaining expected optimal solutions for both investigation phases.
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**Table 6.6: Optimization results of FSCABC and ABC algorithms for 30 runs**

<table>
<thead>
<tr>
<th>Objective</th>
<th>Optimization function</th>
<th>ESS real &amp; reactive powers and locations</th>
<th>Objective</th>
<th>Optimization function</th>
<th>ESS real &amp; reactive powers and locations</th>
</tr>
</thead>
<tbody>
<tr>
<td>FSCABC best</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs</td>
<td>$P=1.269 \ Q=0.417$</td>
<td>FSCABC worst</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs</td>
<td>$P=1.322 \ Q=0.333$</td>
</tr>
<tr>
<td>FSCABC mean</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs</td>
<td>$P=1.296 \ Q=0.387$</td>
<td>FSCABC $\sigma$</td>
<td>25032.807</td>
<td></td>
</tr>
<tr>
<td>ABC best</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs</td>
<td>$P=1.288 \ Q=0.390$</td>
<td>ABC worst</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs</td>
<td>$P=1.337 \ Q=0.301$</td>
</tr>
<tr>
<td>ABC mean</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs</td>
<td>$P=1.315 \ Q=0.338$</td>
<td>ABC $\sigma$</td>
<td>31082.370</td>
<td></td>
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</table>

Distributed ESS placement for a uniform ESS size (investigation phase-I)

<table>
<thead>
<tr>
<th>Objective</th>
<th>Optimization function</th>
<th>ESS real &amp; reactive powers and locations</th>
</tr>
</thead>
<tbody>
<tr>
<td>FSCABC best</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs</td>
<td>$P=1.269 \ Q=0.417$</td>
</tr>
<tr>
<td>FSCABC worst</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs</td>
<td>$P=1.322 \ Q=0.333$</td>
</tr>
<tr>
<td>FSCABC mean</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs</td>
<td>$P=1.296 \ Q=0.387$</td>
</tr>
<tr>
<td>ABC best</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs</td>
<td>$P=1.288 \ Q=0.390$</td>
</tr>
<tr>
<td>ABC worst</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs</td>
<td>$P=1.337 \ Q=0.301$</td>
</tr>
<tr>
<td>ABC mean</td>
<td>ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs</td>
<td>$P=1.315 \ Q=0.338$</td>
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Table 6.6 continues

<table>
<thead>
<tr>
<th>Optimization &amp; Statistics</th>
<th>ESS real &amp; reactive powers and locations</th>
<th>( % \text{VDI} )</th>
<th>Total Flicker (MW)</th>
<th>( % \text{LLT} )</th>
<th>Total ESS size (MWh)</th>
<th>Objective function value ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>FSCABC</strong></td>
<td>Distributed ESS placement for non-uniform ESS sizes (Investigation phase - II)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>best</strong></td>
<td>ESS7: P=1.491 Q=0.231; ESS8: P=1.284 Q=0.231; ESS10: P=0.703 Q=0.231; ESS11: P=0.851 Q=0.231; ESS12: P=1.258 Q=0.231; ESS15: P=1.094 Q=0.231</td>
<td>51.205</td>
<td>13.093</td>
<td>0.0596</td>
<td>0.042</td>
<td>201.322</td>
</tr>
<tr>
<td><strong>worst</strong></td>
<td>ESS7: P=1.504 Q=0.222; ESS8: P=1.413 Q=0.222; ESS10: P=0.713 Q=0.222; ESS11: P=0.864 Q=0.222; ESS12: P=1.038 Q=0.222</td>
<td>51.684</td>
<td>13.07</td>
<td>0.0595</td>
<td>0.0416</td>
<td>203.168</td>
</tr>
<tr>
<td><strong>mean</strong></td>
<td>ESS7: P=1.500 Q=0.227; ESS8: P=1.284 Q=0.227; ESS10: P=0.701 Q=0.227; ESS11: P=0.869 Q=0.227; ESS12: P=1.249 Q=0.227</td>
<td>51.606</td>
<td>13.098</td>
<td>0.0595</td>
<td>0.042</td>
<td>202.661</td>
</tr>
<tr>
<td><strong>σ</strong> FSCABC</td>
<td>ESS7: P=1.500 Q=0.227; ESS8: P=1.284 Q=0.227; ESS10: P=0.701 Q=0.227; ESS11: P=0.869 Q=0.227; ESS12: P=1.249 Q=0.227</td>
<td>31969.112</td>
<td></td>
<td></td>
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<tr>
<td><strong>ABC</strong></td>
<td>ESS7: P=1.500 Q=0.227; ESS8: P=1.284 Q=0.227; ESS10: P=0.701 Q=0.227; ESS11: P=0.869 Q=0.227; ESS12: P=1.249 Q=0.227</td>
<td>51.606</td>
<td>13.093</td>
<td>0.0595</td>
<td>0.0419</td>
<td>201.484</td>
</tr>
<tr>
<td><strong>best</strong></td>
<td>ESS7: P=1.626 Q=0.222; ESS8: P=1.395 Q=0.222; ESS10: P=0.739 Q=0.222; ESS11: P=0.866 Q=0.222; ESS12: P=1.208 Q=0.222; ESS15: P=1.249 Q=0.227; ESS22: P=0.712 Q=0.227</td>
<td>53.049</td>
<td>13.013</td>
<td>0.0589</td>
<td>0.0414</td>
<td>204.549</td>
</tr>
<tr>
<td><strong>worst</strong></td>
<td>ESS7: P=1.552 Q=0.222; ESS8: P=1.395 Q=0.222; ESS10: P=0.739 Q=0.222; ESS11: P=0.866 Q=0.222; ESS12: P=1.208 Q=0.222; ESS15: P=1.187 Q=0.222; ESS22: P=0.712 Q=0.222; ESS25: P=3 Q=0.222; ESS27: P=0.707 Q=0.222; ESS29: P=0.789 Q=0.222; ESS30: P=3 Q=0.228; ESS31: P=0.706 Q=0.228; ESS32: P=1.208 Q=0.218</td>
<td>53.812</td>
<td>13.052</td>
<td>0.0594</td>
<td>0.0419</td>
<td>204.055</td>
</tr>
<tr>
<td><strong>mean</strong></td>
<td>ESS7: P=1.552 Q=0.222; ESS8: P=1.395 Q=0.222; ESS10: P=0.739 Q=0.222; ESS11: P=0.866 Q=0.222; ESS12: P=1.208 Q=0.222; ESS15: P=1.187 Q=0.222; ESS22: P=0.712 Q=0.222; ESS25: P=3 Q=0.222; ESS27: P=0.707 Q=0.222; ESS29: P=0.789 Q=0.222; ESS30: P=3 Q=0.228; ESS31: P=0.706 Q=0.228; ESS32: P=1.208 Q=0.218</td>
<td>53.812</td>
<td>13.052</td>
<td>0.0594</td>
<td>0.0419</td>
<td>204.055</td>
</tr>
<tr>
<td><strong>σ</strong> ABC</td>
<td>ESS7: P=1.552 Q=0.222; ESS8: P=1.395 Q=0.222; ESS10: P=0.739 Q=0.222; ESS11: P=0.866 Q=0.222; ESS12: P=1.208 Q=0.222; ESS15: P=1.187 Q=0.222; ESS22: P=0.712 Q=0.222; ESS25: P=3 Q=0.222; ESS27: P=0.707 Q=0.222; ESS29: P=0.789 Q=0.222; ESS30: P=3 Q=0.228; ESS31: P=0.706 Q=0.228; ESS32: P=1.208 Q=0.218</td>
<td>8247340.072</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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</table>
6. OPTIMAL ESS ALLOCATION AND SIZING TO IMPROVE PERFORMANCE AND POWER QUALITY OF DISTRIBUTION NETWORKS

Table 6.7: Convergence and computation time of FSCABC and ABC approaches

<table>
<thead>
<tr>
<th>Investigation type</th>
<th>FSCABC convergence</th>
<th>FSCABC computation time (s)</th>
<th>ABC convergence</th>
<th>ABC computation time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>After 206 iterations</td>
<td>378</td>
<td>After 279 iterations</td>
<td>620</td>
</tr>
<tr>
<td>II</td>
<td>After 294 iterations</td>
<td>562</td>
<td>After 413 iterations</td>
<td>818</td>
</tr>
</tbody>
</table>

Figure 6.14: Convergence graph of FSCABC and ABC algorithms.

The computer that is used for the simulation study possesses the following configuration: Windows 10 (64-bit), Intel(R) Xeon 3.5 GHz processor, and 16 GB RAM. For two investigation phases, the convergence characteristics of both the FSCABC and ABC optimization algorithms are illustrated in Fig. 6.14, while the computation time is listed in Table 6.7. Table 6.7 demonstrates that the FSCABC-based technique converges after 206 and 294 iterations for investigation phase-I and investigation phase-II, respectively. In contrast, the ABC approach converges after 279 and 413 iterations during investigation phase-I and investigation phase-II, respectively. In particular, the FSCABC-based optimization approach converges faster than the ABC algorithm. In real time, FSCABC and ABC algorithms take about 378 s and 620 s, respectively, for placing the ESSs during investigation phase-I. For investigation phase-II, the FSCABC and ABC algorithms require around 562 s and 818 s, respectively, for allocating the ESSs on the distribution network.
6.6.4.5 Overall performance and power quality analysis

Table 6.8 compares the performance indices of the system which are estimated according to Section 6.5.3. Generally, $V_{PII} > 1$ indicates that the system has good voltage profile. On the contrary, the higher values of $PLRI_P$, $PLRI_Q$, $PLRI_T$, and $LLI$ imply higher real, reactive, total power losses, and line loading, respectively. Similarly, higher values of $FMI_{Cont}$, $FMI_{STS}$, $FMI_{LTS}$, $FMI_T$, and $RVCI$ denote higher flickers in the system. The $V_{PII} = 1.248$ for Case 3 indicates that this case has good voltage profile which is better than Case 2 ($V_{PII} = 1.200$). All other performance indices are lower during Case 3 compared to Case 2, which suggests that Case 3 provides better performance than Case 2. The results of the above indices are presented in Table 6.8, which suggests that Case 2 and Case 3 have improved the power quality of the system. Case 3 has better power quality than Case 2 (Higher $PQII$ signifies higher power quality of the system).

![Comparison of various cases in relation to performance and cost.](image)

**Figure 6.15:** Comparison of various cases in relation to performance and cost.

The comparison of various cases, in relation to overall performance and total ESS unit cost, is depicted in Fig. 6.15. This figure suggests that the ESS placement using non-uniform ESS sizes (Case 3) improves the system performance better than a uniform sizing approach (Case 2), by minimizing voltage deviation, flicker, power losses, and
6. OPTIMAL ESS ALLOCATION AND SIZING TO IMPROVE PERFORMANCE AND POWER QUALITY OF DISTRIBUTION NETWORKS

Table 6.8: Performance and power quality indices for various cases

<table>
<thead>
<tr>
<th>Case Details</th>
<th>VPI</th>
<th>FMI&lt;sup&gt;Cont&lt;/sup&gt;</th>
<th>FMI&lt;sup&gt;StSw&lt;/sup&gt;</th>
<th>FMI&lt;sup&gt;LTSw&lt;/sup&gt;</th>
<th>FMI&lt;sup&gt;T&lt;/sup&gt;</th>
<th>RVCII</th>
<th>PLRII</th>
<th>LLI</th>
<th>PQI</th>
<th>PQII</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Case 2</td>
<td>1.200</td>
<td>0.921</td>
<td>0.922</td>
<td>0.922</td>
<td>0.935</td>
<td>0.742</td>
<td>0.773</td>
<td>0.757</td>
<td>0.842</td>
<td>0.907</td>
</tr>
<tr>
<td>Case 3</td>
<td>1.248</td>
<td>0.897</td>
<td>0.894</td>
<td>0.894</td>
<td>0.911</td>
<td>0.556</td>
<td>0.504</td>
<td>0.536</td>
<td>0.748</td>
<td>0.881</td>
</tr>
</tbody>
</table>

line loading. However, this approach (Case 3) involves a higher investment cost of the distribution system compared to Case 2. It should be noted here that this research did not perform any cost analysis or cover any financial impacts, which could add another constraint in the objective function and investigated in future works.

6.7 Conclusions

This chapter has presented an effective strategy for optimal allocation of distributed ESSs in distribution networks employing the FSCABC optimization method. The key problems associated with voltage deviation, flicker, power losses, and line loading are minimized. The results attained from the FSCABC technique are verified through the application of the ABC algorithm. Performance improvements of the system are evaluated through related performance indices. The main conclusions are:

- The improvement in system performance is achieved through both approaches—optimal allocation of distributed ESSs through uniform and non-uniform sizing approaches.
- Improvement of the voltage profile and minimization of flicker disturbances are achieved through the PQ injection of ESSs, and thereby power quality of the distribution network is improved.
- The proposed optimal ESS allocation strategy can be employed for asset management applications and distribution network planning.

As with most meta-heuristic approaches, the FSCABC algorithm has some limitations in determining the most optimal solution compared to traditional linear approaches. However, due to the computational burdens involved in using traditional linear optimization search methods, the FSCABC approach has been applied in this study. Regarding future research, more power quality parameters such as over voltage, under voltage, and
interruptions (short term and long term) can be incorporated for overall power quality analysis. Furthermore, sensitivity analyses on the ESS placement, development of optimal operation strategy of distributed ESSs that considers RES uncertainties and the impact on ESS lifetime, detailed analysis regarding cost or financial impacts of the obtained ESS sizes, and intelligent control methods via the on-line communication among the placed ESSs can be targeted.
Chapter 6 references


CHAPTER 6 REFERENCES


Chapter 7

Optimal Sizing of a Grid-scale ESS in Transmission Networks to Improve Frequency Response

The frequency response of a large power system is affected by the penetration of renewable energy sources (RESs), where a grid-scale energy storage system (ESS) can alleviate the problem. This chapter presents a strategy for sizing an ESS to improve frequency response of transmission networks. The location of the ESS in the transmission network is determined through a sensitivity analysis targeting minimum line loading around a bus. The ESS sizing strategy considers the minimization of frequency deviation as well as rate of change of frequency (ROCOF) after generator or load tripping events. The proposed approach is tested in a modified IEEE-39 bus power system considering a variety of scenarios where RESs are integrated as four different schemes for peak and off-peak load conditions. DIgSILENT PowerFactory is used for developing, testing, and analyzing the system models. A fitness-scaled chaotic artificial bee colony (FSCABC) optimization algorithm (a hybrid meta-heuristic approach) is used for optimization through a Python script automating simulation events in PowerFactory. The results obtained from the FSCABC approach are verified through the application of a particle swarm optimization (PSO) algorithm. The simulation results suggest that the proposed ESS sizing technique can successfully improve the frequency response of a transmission network.
7. OPTIMAL SIZING OF A GRID-SCALE ESS IN TRANSMISSION NETWORKS TO IMPROVE FREQUENCY RESPONSE

7.1 Introduction

The industrial development of RESs has increased due to concerns for climate change, energy security, and sustainability. According to REN21’s global status report 2018, a total of 2195 GW of renewable power has been added globally since 2017 [1]. The high penetration of RESs into present power systems replaces conventional fossil fuel-based power plants. Such replacements affect the power system frequency. ESSs can be used as key tools to facilitate RES integration and solve various issues of power networks as presented in [2–6].

Recently, the deployment of ESSs to improve frequency response has attracted the attention of both academia and industry [7], [8]. More specifically, the frequency regulation issue is considered as a key concern by the transmission system operator (TSO) to ensure safe and reliable operation of the networks. According to Order 755 and revised Order 819, enacted by the U.S. Federal Energy Regulatory Commission (FERC), ESSs (e.g., batteries) can bid for accurate and fast frequency response, where a market-based procurement of primary frequency response service is permitted [9, 10]. However, finding an optimal size of utility-scale ESSs for improving frequency response of a transmission network is an essential task in case of planning. Therefore, the motivation of this study is to determine optimal size of a battery energy storage system (BESS) to improve frequency response of transmission networks. Many studies have already been conducted regarding ESS placement and sizing in power systems.

A comprehensive review of ESS applications in power networks is presented in [11] focusing on ESS placement, sizing, operation, and power quality. In [12], siting and sizing of large-scale BESSs are accomplished in RES-integrated transmission networks to minimize the daily production costs. In [13], a DC optimal power flow framework is presented to optimize ESS size, placement, and operation in transmission-constraint networks. Another framework for optimizing the location and sizes of ESSs in a transmission network is proposed to reduce network congestion and facilitate RES (wind) integration in [14].

An ESS sizing approach is presented in [15] to improve the frequency response of a wind-penetrated power system. In [10], a frequency control framework is presented
by integrating ESSs as faster-acting devices to improve frequency regulation of power systems. In that paper, a droop-based strategy with the feedback of the state of charge (SOC) is proposed to control the frequency, where the ESS coordinates the frequency controls of operating generators. In [16], an approach using the controllable loads such as heat pump water heaters and electric vehicles (together) is proposed to support system frequency and reduce the capacity of BESSs. In [17], a BESS capacity is optimized to provide a primary frequency support, while the approach is validated through numerical simulations based on historic frequency measurements and fulfilling grid code requirements. In [7], an economic optimization strategy of the parameters of LiFePO4 BESSs is presented for frequency response in the UK power system. As the BESS provides required real power (MW) to improve the frequency response, parameter tuning of active and reactive power (PQ) controller of a BESS is an important task. Although various efforts were made by the aforementioned studies, optimizing the size of a grid-scale ESS through minimizing frequency deviation and ROCOF, and tuning of PQ controller parameters (of the ESS) has attracted little attention. However, this is one of the important targets of the TSO and this research addresses that need.

This research presents a strategy to determine overall size of a BESS to improve frequency response of a transmission network. A comprehensive investigation is conducted for finding optimal BESS size applying a hybrid meta-heuristic approach namely—FSCABC algorithm [18, 19]. DIgSILENT PowerFactory is used for system modeling and analysis, and Python programming language is employed to control the system models and facilitate optimization. The main contributions of this chapter are summarized as follows:

- A sensitivity analysis is performed for placing the BESS (with the maximum BESS size) on the network focusing on minimum line loading.

- The BESS size is optimized to improve frequency response by minimizing the frequency deviation and ROCOF. The optimal BESS size is sought by restricting the frequency response with frequency nadir ($f_{nadir}$) constraint and thus BESS size is controlled. Different levels of RES-penetration (e.g., around 15% and 30% of total non-renewable generation) are considered, where the impact of incremental RES-integration on frequency response as well as BESS sizing are analyzed. The overall test is performed on 6 different scenarios under peak and off-peak load.
conditions, and the optimal BESS size is decided from the worst case amongst all case studies.

- The parameter tuning of the PQ controller related to real power part \((K_P \text{ and } T_{ip})\) is performed during optimization run, while \(K_P\) and \(T_{ip}\) are included as decision variables \(\beta \text{ and } \gamma\), respectively.

- Moreover, results obtained from FSCABC optimization technique are verified using the PSO approach.

### 7.2 BESS modeling

The BESS model used in this study is a dynamic model (provided by DIgSILENT PowerFactory), which is modified according to system requirements. The overall BESS model is illustrated in Fig. 7.1. The BESS works as a unity power factor (p.f.) system which consists of three main controllers. The frequency controller and the PQ controller are described in following sections. The details of the BESS model including the charge controller can be found in \([20–22]\) and some basic parameters are presented in Chapter 7 Appendix (Table 7.7). The SOC of the model \((SOC_{BESS})\) is calculated using (7.1).

![Figure 7.1: Overall model of the BESS [21].](image-url)
7.2 BESS modeling

\[ U_{DC} = U_{max} \cdot SOC_{BESS} + U_{min} \cdot (1 - SOC_{BESS}) - I \cdot Z_i \]  

(7.1)

where, \( U_{DC} \) = output DC voltage of the BESS (V), \( U_{max} \) = cell voltage of a fully loaded cell (V), \( U_{min} \) = cell voltage of a discharged cell (V), \( Z_i \) = impedance at different operational states, and \( I \) = battery current (A).

The \( SOC_{BESS} \) is subject to (7.2), and \( SOC_{BESS} = 1 \) and \( SOC_{BESS} = 0 \) indicate that the BESS is fully charged and discharged, respectively. Minimum charging current and threshold voltage for \( i_{q-ref} \) used in this model are 0.1 p.u. and 1 p.u., respectively [21].

\[ 0.2 \leq SOC_{BESS} \leq 1 \]  

(7.2)

The frequency controller is a drooped-based controller where the droop defines the amount of active power to be delivered in case of a frequency deviation. The controller
is illustrated in Fig. 7.2. The PQ controller consists of two proportional-integral (PI) controllers such as PI1 and PI2 for active and reactive power, respectively, as shown in Fig. 7.1 and Fig. 7.3. The PI controllers regulate the d and q-axis current components \((i_d-ref_{in} & i_q-ref_{in})\) for the charge controller. The parameters of the PQ controller tuned by DIgSILENT PowerFactory are provided in Table 7.1. However, further tuning of parameters \(K_p\) and \(T_{ip}\) (active part of the PQ controller) is required for better frequency response, as the BESS improves the response by providing necessary active power.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>(T_r)</th>
<th>(T_{rq})</th>
<th>(K_p)</th>
<th>(T_{ip})</th>
<th>AC deadband</th>
<th>(K_q)</th>
<th>(T_{iq})</th>
<th>(i_d-min)</th>
<th>(i_q-min)</th>
<th>(i_d-max)</th>
<th>(i_q-max)</th>
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<tr>
<td>Values</td>
<td>0.01</td>
<td>0.1</td>
<td>2</td>
<td>0.2</td>
<td>0.1</td>
<td>2</td>
<td>-1</td>
<td>-1</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

### 7.3 Problem formulation

#### 7.3.1 Sensitivity function for placing the BESS

The BESS can be placed at any bus of a transmission network to contribute to frequency response improvement without violating the loading limit of a line connected to that bus. To fulfill that objective a sensitivity function is formulated. The sensitivity function \((\beta(\text{Sen}))\) for placing the BESS in the network is defined in (7.3), which determines the BESS position on the network based on minimum \% line loading \((\xi)\). The parameter \(\lambda_n\) represents the BESS location connected to \(n\)th bus of the network. The sensitivity function ensures the BESS placement through avoiding the overloading problem of a line (i.e. \(\xi\) must be within rated line loading \(\xi_{rated}\)) in the transmission network.

\[
\beta(\text{Sen}) = \frac{\delta \xi}{\delta \lambda_n} \cdot \Delta \lambda_n \quad \forall \xi \leq \xi_{rated}
\]  

(7.3)

In particular, the algorithm to allocate the BESS includes the following steps:

1. First, a load flow for the base case (without ESS placement) is conducted and the \(\xi\) for each line is obtained.
7.3 Problem formulation

2. Second, a maximum size (MVA), equal to the upper bound of decision variable $\alpha$ ($UB_1$), is set to the BESS.

3. Thirdly, the BESS is allocated to a bus where minimum $\xi$ value of the connected line is found. The sensitivity test of that BESS location is performed using (7.3) (another load flow is conducted) and $\xi$ value is checked.

4. Finally, the sensitivity test is continued for other locations around the minimum loading zone until the optimal BESS location is obtained.

7.3.2 Objective function for BESS sizing

The objective function of the proposed BESS sizing problem is presented in (7.4). This function mainly determines the optimal BESS size by minimizing ROCOF and frequency deviation ($f_{dev}$) for a given time period ($T$) during a simulation run. Figure 7.4 illustrates a typical frequency response where ROCOF in addition to the area of the curve are targeted to be minimized by (7.4).

![Figure 7.4: Realization of the objective function for a under-frequency problem.](image)

\[
J(C_{Obj}) = \min \left\{ \text{ROCOF}(\alpha, \beta, \gamma) + \sum_{t=0}^{T} \left| f_{nom} - f_{sys}^t(\alpha, \beta, \gamma) \right| / f_{dev} \right\} \tag{7.4}
\]

where, the parameter values are in p.u., $f_{nom}$ = nominal frequency, $f_{sys}^t$ = system frequency at time $t$, and $\alpha$, $\beta$, and $\gamma$ are the decision variables for the BESS size (MVA), $K_p$, and $T_{ip}$, respectively.
7.3.3 Objective function constraints

The objective function of (7.4) is subject to (7.5) to (7.10) along with (7.2):

\[ P_{Gen}^i + \sum_{j \in J^+} (P_{Del}^{j \rightarrow i}) = P_{Con}^i + \sum_{k \in J^-} (P_{Del}^{i \rightarrow k}) \]  \hspace{1cm} (7.5)

\[ Q_{Gen}^i + \sum_{j \in J^+} (Q_{Del}^{j \rightarrow i}) = Q_{Con}^i + \sum_{k \in J^-} (Q_{Del}^{i \rightarrow k}) \]  \hspace{1cm} (7.6)

\[ \text{ROCOF}_{\text{min}} < |\text{ROCOF}| < \text{ROCOF}_{\text{max}} \]  \hspace{1cm} (7.7)

\[ f_{\text{nadir}-\text{min}} < |f_{\text{sys}}| < f_{\text{nadir}-\text{max}} \]  \hspace{1cm} (7.8)

\[ P_{\text{BESS}}^\text{min} < P_{\text{BESS}} < P_{\text{BESS}}^\text{max} \]  \hspace{1cm} (7.9)

\[ P_{\text{BESS},c}^l \leq P_{\text{BESS}}^l \leq P_{\text{BESS},d}^l \]  \hspace{1cm} (7.10)

where,

- (7.5) and (7.6) ensure the real and reactive power balances of a bus \( i \), respectively [2].
- (7.7) guarantees that the ROCOF during the simulation study must be within the maximum and minimum limits (\( \text{ROCOF}_{\text{max}} \) & \( \text{ROCOF}_{\text{min}} \)) \( \pm 0.5 \text{ Hz/s} \) [23].
- (7.8) ensures that the \( f_{\text{sys}} \) of the attained frequency response must be within the maximum and minimum limits (\( f_{\text{nadir}-\text{max}} \) & \( f_{\text{nadir}-\text{min}} \)) 51 Hz to 48.75 Hz [24].
- The BESS supplies required active power for fast recovery (in secs) of frequency deviation during network events. Hence, (7.9) and (7.10) indicate that the power (\( P_{\text{BESS}} \)) of the BESS should not exceed the limits (\( P_{\text{BESS}}^\text{min} \) & \( P_{\text{BESS}}^\text{max} \)) during charging and discharging phases. In addition, the BESS operation within the SOC limits is ensured by (7.2) [2].

7.4 Optimization and proposed approach

7.4.1 FSCABC optimization approach

In this research, the grid-connected BESS sizing problem is optimized by applying an FSCABC algorithm whose overall steps are represented in Fig. 7.5. The FSCABC
7.4 Optimization and proposed approach

Figure 7.5: Flowchart of the FSCABC approach.

hybridizes two useful techniques- (1) the fitness scaling technique and (2) the chaotic technique [18, 19] with artificial bee colony (ABC) algorithm. The fitness scaling and chaotic techniques are defined by (7.11) and (7.12), respectively [18, 19].

\[
fit_i^{Scale} = \frac{r_i^m}{\sum_{i=1}^{SN} r_i^m}
\]  
(7.11)
where, \( r_i \) is the rank of \( i \)th individual bee, \( SN \) is the number of food source, and \( m \) is the exponential value for power computation.

\[
x_i^{n+1} = \mu x_i^n (1 - x_i^n), \quad i = 1, 2, \ldots, SN
\]  

(7.12)

where, \( n \) is the iteration number, \( x_i^n \) is the \( i \)th chaotic variable, and \( \mu^{Bif} \) is the bifurcation parameter of the system with \( \mu^{Bif} \in [0, 4] \). The chaotic behaviour is revealed with \( \mu^{Bif} = 4, \ x_0 \in (0, 1), \) and \( x_0 \notin \{0.25, 0.5, 0.75\} \). The detail formulation of the ABC algorithm can be found in [2]. The ABC algorithm works in three different phases including employed bee, onlooker bee, and scout bee phases. The algorithm is initialized with the colony size \( CS \) of solutions \( x_{ij} (i = 1, 2, \ldots, SN; \ j = 1, 2, \ldots, D) \) \( (D = \) problem dimension) by fulfilling \( CS = \) employed bees \( (N_{Emp}) + \) onlooker bees \( (N_{Onl}) \). The population is initialized with \( j = 0 \) as given in (7.13).

\[
x_{i0} = LB + \psi_{ij}^{RAN} (UB - LB), \quad i = 1, 2, \ldots, SN
\]  

(7.13)

where, \( \psi_{ij}^{RAN} \) signifies a random number within \([0, 1]\) and \( UB \ & LB \) represent upper and lower bounds, respectively. Each employed bee travels from \( x_{ij} \) (old position) to \( v_{ij} \) (new position) by applying (7.14).

\[
v_{ij} = x_{ij} + \Phi_{ij}^{RAN} (x_{ij} - x_{kj})
\]  

(7.14)

In (7.14), \( \Phi_{ij}^{RAN} \) signifies a random uniform number within the range \([-1, 1]\). The \( x_{ij} \) is replaced with new \( v_{ij} \) only if \( v_{ij} \) is improved compared to \( x_{ij} \), otherwise \( x_{ij} \) remains unchanged. The fitness values \( F_{fit}^{FdS} \) and \( p_{i}^{FdS} \) in relation to food sources of employed bees are computed as per (7.15) and (7.16), respectively, where, \( f(x_i)^{ObF} \) = values of the objective function to be optimized.

\[
F_{fit}^{FdS} = \begin{cases} 
\frac{1}{1 + f(x_i)^{ObF}}, & f(x_i)^{ObF} \geq 0 \\
1 + |f(x_i)^{ObF}|, & f(x_i)^{ObF} < 0
\end{cases}
\]  

(7.15)

\[
p_{i}^{FdS} = \frac{F_{fit}^{FdS}}{\sum_{j=1}^{SN} F_{fit}^{FdS}}
\]  

(7.16)
7.4 Optimization and proposed approach

Following this, the onlooker bee finds a new location using (7.17) based on $p_i^{Fds}$ value, where, $\omega_i^{Emp} = \text{weight coefficient regarding employed bee phase.}$

$$v_{ij} = x_{ij} + \omega_i^{Emp} \Phi_{ij}^{Rand} (x_{ij} - x_{kj})$$  \hspace{1cm} (7.17)

The chaotic sequence of the key factor for convergence in ABC ($\Phi$) is described by (7.18) [18].

$$\Phi_{ij}^{Chaos} = 2 \times [4\Phi_{ij} (1 - \Phi_{ij})] - 1$$  \hspace{1cm} (7.18)

In scout bee phase, the discarded solutions are improved and replaced by a new solution $x_{ij}^{Chaos}$ as defined in (7.19).

$$x_{ij}^{Chaos} = \min(x_{ij}) + \varphi_{ij} [\max(x_{ij}) - \min(x_{ij})]$$  \hspace{1cm} (7.19)

where, $\max(x_{ij}) = \max\{x_{1j}, x_{2j}, ..., x_{Nj}\}$, $\min(x_{ij}) = \min\{x_{1j}, x_{2j}, ..., x_{Nj}\}$, and $\varphi_{ij} = \text{a random number in the range [-1, 1].}$ Similar to parameter $\Phi$, the chaotic sequence of $\varphi_{ij}$ is defined by (7.20) and utilized into (7.19).

$$\varphi_{ij}^{Chaos} = 4\varphi_{ij} (1 - \varphi_{ij})$$  \hspace{1cm} (7.20)

7.4.2 Proposed approach

The methodology for the proposed BESS sizing is depicted in Fig. 7.6. After placing the BESS on the network (performing the sensitivity test), the FSCABC optimization parameters and bounds are set as summarized in Table 7.2. Then the FSCABC optimization process is started through the nomination of parameters $\alpha$, $\beta$, and $\gamma$ within their limits and step sizes as specified in Table 7.2. The BESS supplies required active power for the network to improve frequency response. Hence, the parameters $\beta$ and $\gamma$ are introduced in optimization for tuning parameter $K_p$ and $T_{ip}$ of the PQ controller, respectively. If the load flow with this parameter setting is successful, then dynamic simulation is conducted based on the defined events and through the verification of initial conditions. Of note, the dynamic simulation study is performed in terms of seconds, where the frequency response needs to be recovered immediately after an event to avoid unwanted situations within the network. Hence, during this short course of time (in secs), the RES variability has been ignored in this study. The simulation study
is conducted for a worst-case scenario where maximum RES penetration in each case study is considered to determine the BESS size for recovery of frequency response. The optimization process determines the optimal BESS size to improve frequency response.
(by minimizing the frequency deviation as well as ROCOF) targeting the $f_{\text{nadir}} = 48.751$ Hz during under-frequency period and $f_{\text{nadir}} = 50.999$ Hz during over-frequency period. Thus, this approach restricts the over-sizing problem of the BESS to recover system frequency deviation after a generator outage or a load trip event.

### 7.5 Study system and testing

The proposed approach is tested on the modified IEEE 39-bus power system which is an equivalent transmission system model of the New England area and Canada (in the northeast of the U.S.A.) [25, 26]. The single line diagram of the system is depicted in Fig. 7.7, whose data can be found in [25, 26]. The IEEE-39 bus system has been selected in this research due to the fact that this network is found suitable to investigate proposed approach at a high voltage (HV) transmission level. The complete data of the used IEEE-39 bus system is included in Appendix C (at the end of this thesis). The model is investigated for a system frequency of 50 Hz. To avoid line loading problem, the current rating of Line21-22 (L21-22) is changed to 1.2 kA, and a P of 300 MW and a Q of 50 MVar are shifted from load39 (Ld39) to Ld27. Overall testing is performed in twelve different case studies under peak and off-peak load conditions. These case studies originated from three basic scenarios such as base case (without RESs) and cases with different levels of RES penetration (wind and solar). The solar parks (PVP1=600 MVA and PVP2=420 MVA) and wind parks (WP1=640 MVA, WP2=220 MVA, and WP3=220 MVA) are installed on the network based on the RES schemes as given in TABLE 7.3, while their locations are shown in Fig. 7.7. The ratings of newly added transformers (determined based on system requirements) are XF1=600 MVA, XF2=450 MVA, XF3=700 MVA, XF4= XF5=250 MVA, XF6=500 MVA; while the ratings of newly added bus40 (B40), B41, B42, B43, B44, B45 are same as of B37 (16.5 kV). Generator2 (G2) is the reference machine of the system whose power limits are: $P_{G2\text{max}} = 150$ MW, $P_{G2\text{max}} = 595$ MW, $Q_{G2\text{min}} = -210$ MVar, and $Q_{G2\text{max}} = 490$ MVar. The voltage magnitude and angle of G2 are $V_{G2} = 0.982$ p.u. and $\phi_{V} = 0$ deg, respectively [25, 26]. Two types of events such as largest generator outage (based on largest MW generation) and largest load off are performed. A point to be noted here is that G1 is an interconnection point. Therefore, G9 is considered for performing an outage (as it generates the next largest amount of active power), while Ld39 is taken into account for shutting down.
The required generator dispatch plans for various scenarios (during peak and off-peak conditions) are presented in TABLE 7.3. In this model, built-in templates of PowerFactory for wind park (WP) and solar park (PVP) are installed and simulation events are performed considering their maximum possible generation (worst case scenario). Furthermore, to integrate RESs to the network, the generators are replaced with the same MW size of WPs and PVPs considering worst case scenarios. Two different levels of RES penetration, such as around 15% and 30% of total non-renewable generation, are considered to analyze the incremental RES penetration impact on frequency response during both peak load and off-peak load conditions. The details of load, generator, and transformer models including the case studies are described in the following sections.
Table 7.3: Generator dispatch plans during peak and off-peak periods

<table>
<thead>
<tr>
<th>Generators</th>
<th>MW during peak load condition</th>
<th>MW during off-peak condition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S-I</td>
<td>S-II</td>
</tr>
<tr>
<td>G1</td>
<td>1000</td>
<td>650</td>
</tr>
<tr>
<td>G2 (Ref.)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>G3</td>
<td>650</td>
<td>650</td>
</tr>
<tr>
<td>G4</td>
<td>632</td>
<td>632</td>
</tr>
<tr>
<td>G5</td>
<td>508</td>
<td>508</td>
</tr>
<tr>
<td>G6</td>
<td>650</td>
<td>650</td>
</tr>
<tr>
<td>G7</td>
<td>560</td>
<td>560</td>
</tr>
<tr>
<td>G8</td>
<td>540</td>
<td>Off</td>
</tr>
<tr>
<td>G9</td>
<td>830</td>
<td>830</td>
</tr>
<tr>
<td>G10</td>
<td>250</td>
<td>250</td>
</tr>
<tr>
<td>RESs</td>
<td>No RESs</td>
<td>RES sch-I</td>
</tr>
<tr>
<td>PVP1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>PVP2</td>
<td>-</td>
<td>350</td>
</tr>
<tr>
<td>WP1</td>
<td>-</td>
<td>540</td>
</tr>
<tr>
<td>WP2</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>WP3</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Where, S = Scenario, sch = scheme, Ref. = Reference machine

7.5.1 Details of load, generator, and transformer models

Models and parameters of loads, generators, and transformers used in this study can be found in PowerFactory Technical Reference documents and in [25, 26]. Voltage dependency of load is defined by (7.21) and (7.22) through setting constant current behaviour for $P$ ($k_{pu}$ =1) and constant impedance behaviour for $Q$ ($k_{qu}$ =2) within the voltage range 0.8 p.u. to 1.2 p.u., and dynamic load time constant is set to 0.1s [25, 26].

\[
P = P_{Ldf} \cdot (V/V_{Ldf})^{k_{pu}} \quad (7.21)
\]

\[
Q = Q_{Ldf} \cdot (V/V_{Ldf})^{k_{qu}} \quad (7.22)
\]

The power ratings of the synchronous generators are adapted for achieving realistic inertia time constants and allowing the power dispatch within reasonable governor limits. IEEE Type 1 rotating excitation systems are used as automatic voltage regulators.
(AVRs). Depending on the excitation voltage $E_f$, the feedback block uses a transfer function to model the saturation as defined in (7.23) where $C_1, C_2 =$ saturation factors (p.u.), $K_E =$ exciter constant (p.u.), and $V_{Rmax} =$ controller maximum output (p.u.). Regarding governors (GOVs), IEEE Type G1 (steam turbine) is applied to G2-G9, while IEEE Type G3 (hydro turbine) is used in G10. Being an interconnection point, G1 is modelled with constant excitation and has no AVRs or GOVs. According to [26], the ratings of transformers and tap changers are determined in accordance with generator ratings to build realistic models. In addition, the vector group of all transformers is assumed to be YNy0 [25, 26].

$$y = \frac{E_f \cdot C_2 \cdot exp\left(\frac{\ln(C_2/C_1) \cdot E_f}{V_{Rmax}/(K_E+C_2)}\right)}{exp\left(\frac{\ln(C_2/C_1) \cdot V_{Rmax}/(K_E+C_2)}{V_{Rmax}/(K_E+C_2)}\right) - 0.75 \cdot \frac{V_{Rmax}}{(K_E+C_2)}}$$

(7.23)

### 7.5.2 Case studies during peak load condition

The proposed sizing approach is tested on three basic scenarios during peak load conditions namely, Scenario-I (S-I), S-II, and S-III. Under S-I, two cases such as Case 1 and Case 2 are defined and studied for generator outage and load trip events, respectively. Similarly, Case 3 and Case 4 under S-II, and Case 5 and Case 6 under S-III are defined. Of note, no RESs are integrated during S-I and active power (MW) of all generators are presented in TABLE 7.3. Two RES-schemes are considered during peak load condition, where about 15% and 30% RESs of total generation capacity (as per S-I) replace the non-renewable generation under RES scheme-I and scheme-II, respectively. RES scheme-I is integrated during S-II (as given in TABLE 7.3), while PVP2 = 350 MW and WP1 = 540 MW replace the same MW of G1 and G8, respectively (considering the worst case scenario). In addition to RES scheme-I, more RESs (RES scheme-II) are added during S-III where PVP1 = 508 MW and WP2 + WP3 = 360 MW replace the same MW of G5 and G1, respectively.

### 7.5.3 Case studies during off-peak load condition

Three more scenarios during off-peak load conditions such as S-IV, S-V, and S-VI are considered in this study. It is assumed that the overall load of the network is
7.6 Results and discussion

Reduced by 30% during off-peak condition, and P and Q of the network reduce to 4267.97 MW and 1115.31 MVar, respectively. Based on this load demand, a new generator dispatch plan is made for off-peak period (S-IV, S-V, and S-VI in TABLE 7.3). Two more RES schemes namely- RES scheme-III and RES scheme-IV are considered for S-V and S-VI, respectively. Again, 15% and 30% RESs of total generation capacity (as per S-IV) replace the non-renewable generation during RES scheme-III and scheme-IV, respectively. Similar to peak load, six cases are studied such as Case 7 and Case 8 under S-IV, Case 9 and Case 10 under S-V, and Case 11 and Case 12 under S-VI. During S-IV, no RESs are added to the network. To balance the generation and loads of the network, G3 and G4 shut down, and a total of 284 MW are reduced from G6 and G9. According to TABLE 7.3, RES scheme-III is integrated during S-V, while PVP2 = 270 MW and WP2 + WP3 = 360 MW replace the same MW of G1. In contrast, RES scheme-IV (with more RESs) is added during S-VI where PVP2 + WP2 + WP3 (= 350 MW + 360 MW) = 710 MW and WP1 = 540 MW replace the same MW of G1 and G8, respectively.

7.6 Results and discussion

This section explores the impact of optimal ESS sizing to improve frequency response of a transmission network affected by RES integration and unanticipated events such as large generator outage or large load trip. The performance analysis is conducted for the case studies described in the preceding section. The BESS sizing results are presented in Table 7.4. This section also compares the optimization results attained from FSCABC approach with PSO algorithm. The results of sensitivity analysis and BESS sizing are described in following sections.

7.6.1 Results of sensitivity analysis

According to the sensitivity analysis performed for the worst scenario S-III, minimum line loading (7.846%) is found in L14-15. Hence, the BESS is placed on B14 as it acts as a lightly loaded zone of the network. The sensitivity test with the placed BESS is also performed for other scenarios to monitor the line loading status as presented in Fig. 7.8. This suggests that the BESS can be placed on B14 for other scenarios also (as the $\xi < \xi_{\text{rated}}$) rather than changing the BESS location for each scenario.
7. OPTIMAL SIZING OF A GRID-SCALE ESS IN TRANSMISSION NETWORKS TO IMPROVE FREQUENCY RESPONSE

Figure 7.8: Line loading status of various scenarios after the sensitivity test.

7.6.2 BESS sizing during peak and off-peak load conditions

7.6.2.1 BESS sizing during peak load

The frequency responses for Case 1, Case 3, and Case 5, affected by the outage of G9, are presented in Fig. 7.9(a). The results, indicating under-frequency problems, are presented for both categories—with an ESS (w-ESS) and without an ESS (w/o-ESS). It

Table 7.4: ESS sizing results for various cases

<table>
<thead>
<tr>
<th>Cases</th>
<th>$f_{nadir}$ (Hz) w/o ESS</th>
<th>$f_{nadir}$ (Hz) with ESS</th>
<th>ROCOF (Hz/s) w/o ESS</th>
<th>ROCOF (Hz/s) with ESS</th>
<th>ESS size (MVA)</th>
<th>$K_p$</th>
<th>$T_{ip}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case1</td>
<td>47.658</td>
<td>48.751</td>
<td>0.238</td>
<td>0.224</td>
<td>287.3</td>
<td>100</td>
<td>0.1</td>
</tr>
<tr>
<td>Case2</td>
<td>51.202</td>
<td>50.999</td>
<td>0.253</td>
<td>0.248</td>
<td>212.9</td>
<td>5</td>
<td>0.2</td>
</tr>
<tr>
<td>Case3</td>
<td>47.353</td>
<td>48.751</td>
<td>0.260</td>
<td>0.251</td>
<td>348.2</td>
<td>100</td>
<td>0.2</td>
</tr>
<tr>
<td>Case4</td>
<td>51.335</td>
<td>50.999</td>
<td>0.262</td>
<td>0.254</td>
<td>317.4</td>
<td>5</td>
<td>0.25</td>
</tr>
<tr>
<td>Case5</td>
<td>47.023</td>
<td>48.751</td>
<td>0.291</td>
<td>0.262</td>
<td>409.9</td>
<td>100</td>
<td>0.1</td>
</tr>
<tr>
<td>Case6</td>
<td>51.444</td>
<td>50.999</td>
<td>0.267</td>
<td>0.256</td>
<td>389.3</td>
<td>4</td>
<td>0.3</td>
</tr>
<tr>
<td>Case7</td>
<td>48.078</td>
<td>48.751</td>
<td>0.287</td>
<td>0.270</td>
<td>253.4</td>
<td>100</td>
<td>0.25</td>
</tr>
<tr>
<td>Case8</td>
<td>51.079</td>
<td>50.999</td>
<td>0.197</td>
<td>0.194</td>
<td>66.4</td>
<td>5</td>
<td>0.35</td>
</tr>
<tr>
<td>Case9</td>
<td>47.983</td>
<td>48.751</td>
<td>0.304</td>
<td>0.282</td>
<td>278.6</td>
<td>100</td>
<td>0.1</td>
</tr>
<tr>
<td>Case10</td>
<td>51.095</td>
<td>50.999</td>
<td>0.195</td>
<td>0.192</td>
<td>78.6</td>
<td>8</td>
<td>0.1</td>
</tr>
<tr>
<td>Case11</td>
<td>47.815</td>
<td>48.751</td>
<td>0.310</td>
<td>0.282</td>
<td>337.6</td>
<td>100</td>
<td>0.15</td>
</tr>
<tr>
<td>Case12</td>
<td>51.229</td>
<td>50.999</td>
<td>0.201</td>
<td>0.195</td>
<td>167.8</td>
<td>6</td>
<td>0.2</td>
</tr>
</tbody>
</table>

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7.6 Results and discussion

Figure 7.9: Frequency response for various cases during peak load condition—(a) due to generator outage (b) due to load trip.

is apparent from Fig. 7.9(a) that the $f_{\text{nadir}}$ decreases to 47.658 Hz (without the BESS) after the generator trip for Case 1. This decreases further with RES penetration to 47.353 Hz and 47.023 Hz during Case 3 and Case 5, respectively. These unexpected scenarios are recovered through employing the BESS with a proper size targeting $f_{\text{nadir}} = 48.751$ Hz as depicted in Fig. 7.9(a). The appropriate BESS sizes for Case 1, Case 3, and Case 5 are 287.3 MVA, 348.2 MVA, and 409.9 MVA, respectively, as presented in Table 7.4.

On the other hand, the over-frequency issue arises after tripping of Ld39 and $f_{\text{nadir}}$ increases beyond the desired limit as illustrated in Fig. 7.9(b). The $f_{\text{nadir}}$ after the load trip event goes to 51.202 Hz (Case 2), which further increases through RES penetration
to 51.335 Hz and 51.444 Hz during Case 4 and Case 6, respectively. The appropriate BESS sizes to recover over-frequency issue (i.e. to decrease the $f_{nadir}$ to 50.999 Hz) are 212.9 MVA, 317.4 MVA, and 389.3 MVA for Case 2, Case 4, and Case 6, respectively.

7.6.2.2 BESS sizing during off-peak load

The frequency responses during off-peak load condition are represented in Fig. 7.10. After the outage of G9, the under-frequency problem is analyzed in Case 7, Case 9, and Case 11. According to Fig. 7.10 (a) and Table 7.4, without the utilization of the BESS $f_{nadir}$ decreases to 48.078 Hz, 47.983 Hz, and 47.815 Hz for Case 7, Case 9, and Case 11,
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Figure 7.11: Generator responses for Case 5—(a) active power (b) reactive power.

Figure 7.12: Generator responses for Case 6—(a) active power (b) reactive power.
Figure 7.13: BESS responses (MW) for various cases—(a) during generator outage (b) during load trip.

Figure 7.14: SOC conditions of the BESS for various cases.
7.6 Results and discussion

respectively. The BESS overcomes the situations with an appropriate size for $f_{nadir} = 48.751$ Hz. The proper BESS sizes for Case 7, Case 9, and Case 11 are 253.4 MVA, 278.6 MVA, and 337.6 MVA, respectively. Contrastingly, $f_{nadir}$ increases to 51.079 Hz, 51.095 Hz, and 51.229 Hz for Case 8, Case 10, and Case 12, respectively, after tripping of Ld39 (Fig. 7.10 (b)). The over-frequency problem of Case 8, Case 10, and Case 12 are resolved (to get $f_{nadir} = 50.999$ Hz) by the BESS with sizes of 66.4 MVA, 78.6 MVA, and 167.8 MVA, respectively.

A noticeable point is that the ROCOF of both peak and off-peak load conditions increases with RES penetration and the BESS (having proper size) assists to reduce the ROCOF through optimal settings of $K_p$ and $T_{ip}$ (determined through decision variables $\beta$ & $\gamma$ after optimization). The optimal setting found for $K_p$ during generator outage is 100, while the $T_{ip}$ varies closely. During load trip events, both $K_p$ and $T_{ip}$ vary closely. The real and reactive power responses of generators as well as RESs for Case 5 and Case 6 are depicted in Fig. 7.11 and Fig. 7.12, respectively. The reference machine G2 supplies $P=532.21$ MW and $Q=265.17$ MVar for both Case 5 and Case 6 during normal operation, while the $P$ and $Q$ increase and decrease after the generator and load trip events, respectively. Similarly, all generators contribute $P$ and $Q$ required for the network during the events. Although the generators contribute to the system frequency response, the frequency drops or rises beyond the nadir limits. It is noted here that the RESs do not supply $Q$ as they operate in constant $Q$ mode (Fig. 7.11(b) and Fig. 7.12(b)). The BESS assists to overcome the unexpected situations of a frequency response by providing or consuming required $P$ to or from the network as illustrated in Fig. 7.13. The BESS discharges during under-frequency period caused by the generator outage and supplies the highest $P=360.12$ MW to network for Case 5. On the other hand, it charges during over-frequency period caused by the load trip and consumes the highest $P=271.93$ MW for Case 6. The SOC conditions of the BESS during charging and discharging are depicted in Fig. 7.14. As the SOC at initialization was set to 0.6 (TABLE 7.7), the charging or discharging starts at 0.6 and the BESS provides necessary supports regarding frequency response after the occurrence of network events.

7.6.3 Statistical analysis of FSCABC approach with PSO algorithm

The above investigation shows that the largest BESS size, for the worst case (Case 5) amongst all other cases that are investigated, is 409.9 MVA. The well-known PSO
7. OPTIMAL SIZING OF A GRID-SCALE ESS IN TRANSMISSION NETWORKS TO IMPROVE FREQUENCY RESPONSE

Table 7.5: Optimization results of FSCABC and PSO for 30 runs

<table>
<thead>
<tr>
<th>Optimization statistics</th>
<th>$K_p$</th>
<th>$T_{ip}$</th>
<th>Total ESS size (MVA)</th>
<th>Objective function value (p.u.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FSCABC best</td>
<td>100</td>
<td>0.1</td>
<td>409.929</td>
<td>138.352</td>
</tr>
<tr>
<td>FSCABC worst</td>
<td>100</td>
<td>0.1</td>
<td>409.778</td>
<td>138.377</td>
</tr>
<tr>
<td>FSCABC mean</td>
<td>100</td>
<td>0.1</td>
<td>409.828</td>
<td>138.369</td>
</tr>
<tr>
<td>$\sigma_{FSCABC}$</td>
<td></td>
<td></td>
<td></td>
<td>0.008</td>
</tr>
<tr>
<td>PSO best</td>
<td>100</td>
<td>0.1</td>
<td>410.332</td>
<td>138.285</td>
</tr>
<tr>
<td>PSO worst</td>
<td>100</td>
<td>0.1</td>
<td>409.82</td>
<td>138.370</td>
</tr>
<tr>
<td>PSO mean</td>
<td>100</td>
<td>0.1</td>
<td>410</td>
<td>138.341</td>
</tr>
<tr>
<td>$\sigma_{PSO}$</td>
<td></td>
<td></td>
<td></td>
<td>0.025</td>
</tr>
</tbody>
</table>

Table 7.6: Convergence and computation time of FSCABC and PSO algorithms

<table>
<thead>
<tr>
<th>FSCABC convergence</th>
<th>FSCABC computation time</th>
<th>PSO convergence</th>
<th>PSO computation time</th>
</tr>
</thead>
<tbody>
<tr>
<td>After 110 iterations</td>
<td>880 s</td>
<td>After 137 iterations</td>
<td>1028 s</td>
</tr>
</tbody>
</table>

approach [27, 28] has been utilized in this study to verify this result obtained from the FSCABC algorithm. The details of the PSO algorithm can be found in Chapter 4, Section 4.6.4.3. The PSO settings (as recommended in [29]) are: cognitive and social components = 1.8, inertia weight = 0.6, and population size = 50. The optimization is executed 30 times (for both approaches considering $T=90$ s in the objective function) and thereby the best, mean, and worst solutions of the objective function are attained. Table 7.5 compares the optimization results for Case 5 obtained from both algorithms. Table 7.5 suggests that the minimum of the objective function is reached around 138 p.u. while targeting the $f_{nadir} = 48.751$ Hz. The smaller standard deviation ($\sigma_{FSCABC}$ or $\sigma_{PSO}$) of an approach signifies lower variation among solutions attained from 30 optimization runs. The FSCABC technique is successful in attaining expected optimal solutions as per statistical analysis of Table 7.5.
7.6 Results and discussion

Figure 7.15: Convergence characteristics of FSCABC and PSO algorithms (a) for frequency deviation (b) for ROCOF.

The PC used for the simulation study has the following configuration: Windows 10 (64-bit), Intel (R) Xeon 3.5 GHz processor, and 16 GB RAM. For both optimization approaches, the convergence and the computation time are listed in Table 7.6, while Fig. 7.15(a) and Fig. 7.15(b) illustrate the convergence characteristics (in p.u.) for frequency deviation and ROCOF, respectively. These suggest that the FSCABC-based algorithm converges after 110 iterations, while the PSO algorithm converges after 137 iterations. Regarding computation time, FSCABC and PSO algorithms require about 880 s and 1028 s, respectively, for finding the BESS size.
7.6.4 BESS size in terms of energy rating

From the above analysis it is apparent that obtaining power size of a BESS (MVA) is a sensible approach for frequency support. Hence, the proposed sizing approach is based on nominating BESS power. However, to determine the energy rating associated with the obtained power size, the ratio of 1 (power):1.29 (energy) is assumed. This ratio is nominated based on a successful BESS implementation for frequency control in South Australia by the Hornsdale Power Reserve Battery Energy Storage System [30]. In this study, the evaluated optimal BESS size is 410 MVA or 410 MW (for a unity p.f. system). Therefore, based on this assumption, the energy rating for this solution can be 529 MWh. It should be noted here that the proposed method of this study did not cover any financial impacts or cost analysis, which could be another constraint in the objective function, and might be investigated in future works.

7.7 Conclusions

This chapter has presented an effective strategy for BESS sizing in transmission networks through FSCABC optimization technique. The impact of RES-integration in frequency response and ESS sizing is investigated considering maximum penetration by the RESs (worst case scenario). A sensitivity analysis is performed for placing the BESS. The results obtained from the FSCABC approach are compared with the PSO algorithm. Based on the investigations conducted in this chapter, the following conclusions can be made:

- The proposed grid-scale BESS sizing strategy successfully improves the overall frequency response of a power system by minimizing the frequency deviation and ROCOF.

- Amongst all case studies investigated in this research, the optimal BESS size found for the worst case is 410 MVA (rounded). Multiple BESSs of this total size can also be placed (through the proposed sensitivity approach) to improve the frequency response of a transmission network.
• The tuning of parameters $K_p$ and $T_{ip}$ contributes to frequency response improvement and ROCOF minimization.

Overall, with the considerations of above findings, the proposed ESS sizing strategy is suitable for a transmission system to improve frequency response. For future investigations, financial impacts or cost analysis of the obtained BESS size, the ESS sizing in relation to system inertia, and optimal operation of the ESS in a transmission network can be investigated.

### 7.8 Chapter 7 appendix

**Table 7.7: Parameters of the BESS [21]**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power factor (p.f.)</td>
<td>1</td>
</tr>
<tr>
<td>SOC at initialization (p.u.)</td>
<td>0.6</td>
</tr>
<tr>
<td>Capacity/cell (Ah)</td>
<td>120</td>
</tr>
<tr>
<td>Voltage of an empty cell (V)</td>
<td>12</td>
</tr>
<tr>
<td>Voltage of a full cell (V)</td>
<td>13.85</td>
</tr>
<tr>
<td>No. of parallel cells</td>
<td>800</td>
</tr>
<tr>
<td>No. of cells in a row</td>
<td>870</td>
</tr>
<tr>
<td>Internal resistance/cell (Ω)</td>
<td>0.001</td>
</tr>
<tr>
<td>Droop of frequency controller</td>
<td>0.028</td>
</tr>
<tr>
<td>Dead band of frequency controller</td>
<td>0.0005</td>
</tr>
</tbody>
</table>


Chapter 7 references


REFERENCES


Chapter 8

General Discussions

The proposed study focuses on several power industry issues related to optimal placement and sizing of distributed utility-scale ESSs. The significance of the study is presented in Section 1.2. Although various distribution network issues have been addressed in earlier literature, very few studies have focused on ESS placement that minimizes voltage deviation, real and reactive power losses, and line loading. In addition to the above-mentioned performance parameters, the current study also investigates the impact of ESS placement to minimize network flickers and thereby simultaneously improve performance and power quality. For distribution networks, the study is conducted through the application of both P injection and PQ injection through the ESSs, where performance improvements are evaluated. Additionally, ESS sizing is performed in two different scenarios—using both uniform and non-uniform ESS sizes. Similarly, regarding transmission networks, earlier studies have not considered improvement of frequency response through the minimization of frequency deviation and ROCOF (during ESS sizing process). Correspondingly, this study analyzes the impact of grid-scale BESS sizing in improving frequency response by considering these above factors. Moreover, parameter tuning of the PQ controller of the BESS is performed in this study, which improves the BESS performance significantly. The ABC, FSCABC, and PSO algorithms are used for optimization, where the optimization results are verified through the application of two algorithms.
The specific results of each research objectives have already been discussed in each chapter. This chapter summarizes the fundamental outcomes obtained from this study. In this regard, the key research questions discussed in Chapter 3 are also addressed in the following sections.

8.1 Optimal placement of ESSs using P injection approach

The results of optimal ESS placement using the P injection approach are presented in Chapter 4, demonstrating that the RQ1 is addressed completely. In this study, the IEEE-33 bus is used as a test distribution network. All ESSs of the system work with a unity p.f., which means that the ESSs inject only P to the network ($Q = 0$). The investigation is conducted for peak load condition. During Case 2(I) (with a uniform ESS size), eight ESSs of same size (0.724 MVA) are placed on buses 9, 14, 25, 28, 29, 30, 31, and 32, while eleven ESSs of different sizes are allocated on buses 8, 10, 13, 16, 17, 20, 22, 25, 30, 31, and 32 during Case 3(I) (with non-uniform ESS sizes). The total ESS size obtained from ESS allocation with a uniform ESS size is 5.793 MWh, while it is 7.195 MWh for ESS placement with non-uniform ESS sizes. The results suggest that the proposed approach successfully minimizes the voltage deviation, power losses, and line loading of distribution networks. The evaluated performance indices indicate that the proposed approach improves voltage profiles and minimizes line losses and loading for both uniform (Case 2(I)) and non-uniform ESS sizing (Case 3(I)) compared to the base case (without ESS placement). The $VPII$ for Case 2(I) and Case 3(I) is 1.037 and 1.064, respectively, while $VPII > 1$ indicates good voltage profile. On the other hand, Case 3(I) has the $PLRI_T = 0.802$ and the $LLI = 0.890$ which are lower than those of Case 2(I) ($PLRI_T = 0.816$ & $LLI = 0.894$). This implies that non-uniform ESS sizing (Case 3(I)) achieves improved performance in regards to voltage profile, line losses, and line loading compared to uniform ESS sizing (Case 2(I)). The optimization results obtained from the ABC approach are verified using the PSO algorithm. The total ESS unit cost is also evaluated for each case studies, as the total ESS unit cost is the highest cost component of the system. It is apparent from the analysis of results that case 2(I) is relatively cost effective and is the optimal solution for distributed ESS allocation with a uniform size, while Case 3(I) is the optimal choice for ESS allocation with non-uniform sizes.
8. GENERAL DISCUSSIONS

8.2 Optimal placement of ESSs using PQ injection approach

RQ2 is addressed in Chapter 5 which focuses on optimal ESS placement using the PQ injection approach. The study is performed in the same network scenario of Chapter 4. In this investigation, the ESSs work with variable p.f. (within the range 0.95 to 1) during dispatch and inject both P and Q to the network. Similar to the study of Chapter 4 has been conducted with PQ injection approach, where a new decision variable for Q and some new constraints (equations (5.20) and (5.24)) are introduced. During Case 2 (with a uniform ESS size), eight ESSs of same size (P=0.971 MW and Q=0.291 MVar) are placed on buses 7, 9, 14, 25, 29, 30, 31, and 32, while eleven ESSs of different sizes are allocated on buses 8, 10, 13, 16, 17, 20, 22, 25, 30, 31, and 32 during Case 3(I) (with non-uniform ESS sizes). The optimization results obtained from FSCABC algorithm are verified through the application of ABC, which signifies that the FSCABC successfully attains optimal results. Further, the FSCABC converges faster than the ABC algorithm. The results suggest that the PQ injection-based ESS placement approach performs better than P injection-based approach. The PQ injection approach achieves 11.107% improvement for voltage deviation, 7.995% for line loading, 7.182% for active power loss, 11.127% for reactive power loss, and 8.594% for total line loss over the P injection approach during ESS placement with a uniform ESS size. On the contrary, during ESS placement with non-uniform ESS sizes, the proposed PQ approach attains 7.564% improvement for voltage deviation, 14.858% for line loading, 17.450% for active power loss, 21.772% for reactive power loss, and 18.966% for total line loss compared to the P injection approach. The total ESS size obtained from ESS allocation with a uniform ESS size is 8.109 MWh, while it is 10.666 MWh for ESS placement with non-uniform ESS sizes. It can be noted here that total ESS unit cost attained from the PQ injection approach is higher than that of the P injection approach. Overall, the proposed PQ injection approach achieves higher performance improvement compared to the P injection approach for both investigation categories (uniform and non-uniform ESS sizing), while the PQ injection approach requires higher distribution network investment costs.
8.3 Optimal ESS allocation to improve performance and power quality of distribution networks

In Chapter 6 RQ3 is addressed, where optimal ESS placement is performed using the PQ injection approach as demonstrated in Chapter 5. The same IEEE-33 bus network of Chapter 4 is used as a test network for investigations, where six wind DGs (instead of two WDGs in Chapter 4) and three solar DGs are incorporated (instead of seven solar DGs). The wind DGs inject continuous and switching flickers to the network. In this investigation, the allocation of distributed ESSs is performed with target to simultaneously minimize voltage deviation, line loading and losses, and flickers. During Case 2 (with a uniform ESS size), nine ESSs of same size (P=1.269 MW & Q=0.417 MVar) are placed on buses 7, 9, 14, 24, 25, 29, 30, 31, and 32, while thirteen ESSs with different P and Q values are allocated on buses 7, 8, 10, 13, 15, 22, 24, 25, 27, 29, 30, 31, and 32 during Case 3 (with non-uniform ESS sizes). The total ESS size obtained from Case 2 and Case 3 is 12.022 MWh and 17.572 MWh, respectively. Similar to Chapter 5, the optimization results obtained from the FSCABC algorithm are justified through the application of ABC, which signifies that FSCABC is successful in obtaining optimal results by converging faster than the ABC approach. The performance indices of the system are estimated, while the $V_{PII} = 1.248$ Case 3 indicates that this case has good voltage profile which is better than Case 2 ($V_{PII} = 1.200$). All other performance indices such as $PLRI^P$, $PLRI^Q$, $PLRI^T$, and $LLI$ are lower during Case 3 compared to Case 2, which suggests that Case 3 provides better performance than Case 2. Similarly, flicker minimization indices such as $FMI_{Cont}$, $FMI_{STSw}$, $FMI_{LTSw}$, $FMI^T$, and $RVCII$ are lower for Case 3 compared to Case 2. The results also suggest that both Case 2 and Case 3 have improved the performance as well as power quality of the system compared to the base case. However, Case 3 has better power quality than Case 2 (Higher $PQII$ signifies higher power quality of the system).

The comparison of various cases, in relation to overall performance and total ESS unit cost, suggests that ESS allocation using non-uniform ESS sizes (Case 3) improves system performance and power quality better than a uniform sizing approach (Case 2), by minimizing voltage deviation, flicker, power losses, and line loading. However, this approach (Case 3) involves a higher investment cost of the distribution system compared to Case 2.
8.4 Optimal ESS sizing to improve frequency response of transmission networks

When investigating the optimal sizing of a grid-scale BESS to improve frequency response of transmission networks, every part of RQ4 is addressed. The IEEE-39 bus system is used as a test transmission network, where the RESs (solar and wind parks) are integrated in different levels for various scenarios. Considering worst case scenario (S-III), the grid-scale BESS is placed on bus 14 (based on minimum line loading) which is determined through a sensitivity analysis. In this study, the key issues regarding frequency response such as frequency deviation and ROCOF have been addressed. Moreover, the tuning of two important parameters $K_p$ and $T_i$ has been incorporated in the optimization algorithm that influences the operation of the PQ controller (active power part) for frequency supports. The FSCABC approach has successfully optimized the objective function parameters, whose optimal outcome is verified through the application of the PSO algorithm. The optimization process determines the optimal BESS size to improve frequency response targeting the $f_{\text{nadir}}$ limits 48.751 Hz (during under-frequency period) to 50.999 Hz (during over-frequency period), which restricts the BESS oversizing problem. Accordingly, it is apparent from this investigation that obtaining power size of a BESS (MVA) is a sensible approach for frequency support. For frequency support, the optimal BESS power size obtained by this study is 410 MVA, while the size determined in terms of energy is 529 MWh. Multiple BESSs of this total size can also be placed (through the proposed sensitivity approach) to improve the frequency response of a transmission network.

In summary, this PhD project has investigated several key issues of power networks (both transmission and distribution) and provided solutions through the optimal placement and sizing of utility-scale ESSs. Solving these network issues using the proposed approaches have barely featured in the current literature. In this study, the application of several optimization strategies facilitates the searching process for optimal solutions. More notably, the hybrid meta-heuristic optimization algorithm FSCABC converges faster than ABC and PSO. The integration of large-scale renewables (wind and PVs) with possible impacts has also been addressed in this study. The proposed research could be of benefit to power industries to improve the overall system performance, frequency
8.4 Optimal ESS sizing to improve frequency response of transmission networks

response, and power quality. In this way, an effective ESS placement and sizing strategy can assist network operators towards solving network issues with tractable ESS sizes as well as issues related to investment and sustainable development.
Chapter 9

Conclusions and Future Recommendations

9.1 Conclusions

This thesis investigates the impacts of utility-scale ESS placement and sizing to resolve various issues of power networks in both transmission and distribution levels. To ensure the viability of optimal allocation and sizing of grid-scale distributed ESSs, this thesis has developed several important strategies which can be implemented in modeling, analyzing, and establishing ESS application benefits. Whilst optimizing ESS placement and sizing, this research has also focused on improving performance and power quality of distribution networks, and the frequency response of transmission networks. Thus, this thesis covers both steady-state and transient analyzes of power systems while designing and modeling systems for ESS applications. The application of multiple meta-heuristic optimization approaches (single as well as hybrid) validates the optimality of the obtained results. Two renewable sources (wind and solar PV) are integrated at a large-scale where their impacts are considered during system implementation. The evaluated performance indices assist to monitor performance improvement. Overall, the investigations carried out within this research will benefit both transmission and distribution network operators by providing solutions to recent power industry problems.
9.2 Key findings

The key findings reported in this thesis are summarized as follows:

- This research has conducted a comprehensive literature review in relation to overview of energy storage systems, selection of ESSs, smart charging and discharging rules, optimal placement, sizing, and operation of ESSs. This study has also conducted a literature survey on ESS roles to mitigate various power quality issues. The conducted literature review has provided several important recommendations for future works in terms of ESS applications in power networks, which may benefit researchers around the world.

- This research has used a generic model of grid-scale ESSs for solving distribution network issues. This research has also performed dynamic studies for frequency response analysis through the application of two important and common network events such as generator outage and load trip events. These types of study are required to solve various power network issues in both transmission and distribution levels.

- This research has performed studies on ESS placement and sizing using both P injection and PQ injection approaches. When applying the P injection approach, the ESSs only inject P to the network and dispatch with unity p.f. (i.e., Q=0). On the contrary, the ESSs inject both P and Q to the network during PQ injection approach, i.e., the ESSs dispatch with a variable p.f. (within the range 0.95 to 1 as per Western Australia Technical Rules). The comparison results suggest that the PQ injection approach improves network performance better than the P injection approach through providing more reactive power compensation. However, the distribution system investment cost has been increased using the PQ injection approach. Hence, a tradeoff in relation to performance expectations and costs should be made.

- For ESS sizing two different methods are used: (a) scenario-A where all ESSs of the network have a uniform size, and (b) scenario-B where all ESSs have non-uniform sizes. The comparison results indicate that both sizing approaches are useful during distributed ESS allocations. However, ESS allocation with a uniform
sizing technique can be implemented more flexibly, while the approach with non-uniform ESS sizes is more adjustable with regards to performance improvement.

- This research has addressed some important problems of distribution networks such as voltage deviation, real and reactive power losses, and line loading as performance parameters. In addition, this thesis has proposed a strategy to simultaneously minimize both continuous and switching flickers along with network performance parameters, and thereby improving the performance and power quality of distribution networks. Several performance indices are defined mathematically to evaluate the network performance and power quality, which can be used for performance evaluation.

- For transmission networks, this research has developed a BESS sizing strategy to improve frequency response, where a dynamic simulation study has performed through generator and load trip events under both peak and off-peak load scenarios. Now-a-days, this type of investigation is demanded by transmission system operators, where transmission networks are facing severe frequency issues due to renewable integration as well as various network events. The key problems regarding frequency response such as minimization of frequency deviation and ROCOF have been addressed within this research. Furthermore, this study has performed tuning of parameters $K_p$ and $T_{ip}$ of BESS PQ controller (active power part), which is essential for providing required active power to the network for frequency support. In addition, a sensitivity analysis is performed for allocating the grid-scale BESS in transmission networks based on minimum line loading, which can also be used for placing multiple BESSs (distributed) in the network. The optimal BESS power size found by this study is 410 MVA, while the size obtained in terms of energy is 529 MWh.

- For optimization, this thesis has employed three optimization approaches such as ABC, FSCABC, and PSO algorithms. The optimization codes have been developed using Python that are further applied to automate the simulation events in PowerFactory. The results of each chapter are verified using any two of these approaches. As per investigations conducted in this research, the hybrid meta-heuristic optimization algorithm FSCABC converges faster than ABC and PSO.
9.3 Future recommendations

- The proposed optimal ESS allocation strategies can be employed for asset management applications and both transmission and distribution network planning. As the optimal placement of utility-scale ESSs largely depends on performance improvement targets, a tradeoff should be made in terms of performance indices, installation sites, and costs.

9.3 Future recommendations

This PhD project has considered and addressed a number of issues of power networks, contributing to knowledge in modeling, analyzing, and establishing ESS application benefits. However, there are still several scopes for further studies with the focus on the following research factors:

- Intelligent control techniques can be applied that consider the online communication among the placed ESSs.

- Future works can investigate the development of optimal operation strategy of distributed ESSs that considers RES uncertainties and the impact on ESS lifetime. Various ESS control approaches (e.g., multi-agent system) can be employed to facilitate optimal ESS operation in distribution networks.

- A sensitivity analysis regarding the optimal ESS allocation using both P and PQ injection approaches can be conducted. This type of analysis can also be investigated for optimal operation of ESSs.

- More power quality parameters such as over voltage, under voltage, interruptions (short term and long term), and harmonics can be incorporated for overall power quality analysis through ESS applications.

- It should be noted here that this research did not cover any financial impacts or cost analysis, which could be another constraint in the objective function. Hence, the financial or cost analysis might be investigated for every research questions of this thesis in future works.
9. CONCLUSIONS AND FUTURE RECOMMENDATIONS

- The BESS sizing in relation to system inertia and optimal operation of the BESS in a transmission network can be further investigated. Moreover, optimal ESS sizing can be accomplished by considering other cost factors of distribution networks (which are not addressed in this study) that are directly related to the benefits of selected case studies.

- Although there are various types of ESSs with extensive advantages and disadvantages as discussed in the literature, the optimal choice of ESSs will depend on the expected performance enhancements, ESS characteristics, and application types. While batteries are widely used ESSs in various applications, other ESS technologies can be considered to compare ESS performance in future works. Furthermore, a comparison of the selected ESS (after sizing) with other possible types in regard to cost and performance is recommended to explore an appropriate ESS option for a specific location in a power network.

- For demand-side management and appropriate system modeling with fluctuating loads such as electric vehicles (EVs—which are moveable ESSs) load and EV uncertainties can be considered in the optimal ESS placement problem.

- This research investigates on frequency issues of a transmission network. More research effort can be applied to optimizing other transient/dynamic issues rather than the steady state characteristics of a power network.

- The reliability of a distribution network with ESS applications can be analyzed through the verification of reliability indices such as SAIDI, SAIFI, CAIDI, CTAIDI, CAIFI, MAIFI, ASIFI, ASAI, ASIDI, CEMIn, and CELID.

- The hybridization of one meta-heuristic approach with other optimization algorithms (e.g., PSO) can be applied with proper setting of control parameters. For example, the ABC approach can be hybridized with PSO algorithm and can be utilized for optimization purpose.

- As global warming and pollution are pressing issues, environmental and geographical constraints can be considered along with technical and economic constraints to provide more realistic solutions for optimal ESS placement.
Appendices

The appendices presented in each chapter are not included here again. The other essential parts are added as appendices only.
Appendix A (on DVD): Journal Papers Arising From This Candidature

Copies of the articles arising from this thesis have been included in this appendix. These comprise the following:

**Published works (subject to copyright by the publisher):**

   
   [https://doi.org/10.1016/j.rser.2018.03.068](https://doi.org/10.1016/j.rser.2018.03.068)

   
   [https://doi.org/10.1016/j.apenergy.2018.07.100](https://doi.org/10.1016/j.apenergy.2018.07.100)

**Unpublished works (in review, not to be cited without prior approval from the corresponding author):**


Appendix B (on DVD): Copyright Statements for Using Contents From Published Papers

As this thesis uses contents from published papers (based on outcomes of current research), copyright statements regarding permissions from related journals are included in this Appendix.
Appendix C (on DVD): Complete Network Data Used in Chapter 7

In this appendix, the complete network data of the transmission network model (IEEE-39 bus) of Chapter 7 (which has not included in Chapter 7 Appendix) has been included. This appendix also comprises the complete BESS model used in Chapter 7, which is provided by PowerFactory.
Appendix D is not included in this version of the thesis